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Health-Specific Moral Hazard Effects

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In this paper I examine the effect of insurance on the demand for health care among consumers of similar health, which I call the health-specific moral hazard effect. Using the 2000 Medical Expenditure Panel Survey, I analyze the variation in the moral hazard effect across health subpopulations in the demand for inpatient and outpatient services. The endogeneity of insurance, the change of insurance regime, and the discreteness and the nonnegativity of the use of health care motivate the use of an endogenous switching model for count data. The econometric results indicate that the moral hazard effect for physician visits is higher at relatively higher levels of health, whereas the effect for both hospital nights and hospital admissions is lower at relatively higher levels of health. The evidence suggests that both efficient and inefficient moral hazard may exist, and this may depend on the type of health care service used.

JEL Classification: C25, I11

1. Introduction

Health care consumers do not react to changes in out-of-pocket cost without considering their health. Although many outstanding studies estimate the effect of insurance on health care demand among the general populations, this effect is likely health specific, varying between consumers of different health. Consequently, predicting the effect of health insurance on the demand for health care may be more practical with reference to a specific health subpopulation.[1] In this paper, I analyze the effect of insurance on the demand for health care among consumers of similar health, which I call the "health-specific moral hazard effect."

Health insurance may affect the demand for health care services with varying intensity, since a consumer's preferences toward health may vary by dimension of health. For example, a consumer may exhibit different actions in his decisions toward tertiary care (which may represent mortality) than toward primary care. Consequently, the relationship between the moral hazard effect and health may be dimension dependent and each health state may have different moral hazard profiles across different health care services. This paper examines the potential for such variation in the moral hazard effect in the demand for inpatient and outpatient services.

By estimating health-specific moral hazard effects across health care services, this paper seeks to expand the existing literature on the welfare implications of health insurance. Since health insurance

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[1] Wedig (1988) estimates the price elasticity of health care by health status for ambulatory physician services and finds that although a decrease in health status reduces the elasticity of the initial decision to seek care, it has no effect on the elasticity of demand at mean levels of consumption.

decreases the effective price of health care, thereby creating a wedge between the cost of care and its price, Pauly (1968) argues that additional health care used by the insured (that is, moral hazard) is welfare decreasing. Nyman (1999a, 2003), however, showing that the price subsidy that is used to pay off the health insurance contract incorporates an income transfer from the healthy to the ill, demonstrates that the conventional moral hazard effect contains both inefficient health care use, which is due to the opportunistic price effect, and efficient health care use, which is due to the income transfer that the ill obtains from the healthy and spends in part on additional health care. Thus, the welfare implications of health insurance are ambiguous. By analyzing health-specific moral hazard effects, it may be possible to conclude whether the efficient or the inefficient moral hazard effect dominates for a particular health care service. If additional health care used by insured consumers is higher for better health states compared with relatively worse health states, this suggests that the inefficient moral hazard dominates. If, on the other hand, additional health care used by the insured is higher for relatively worse health states, then the efficient moral hazard may dominate.

The health-specific moral hazard effect may also be of some interest to those who are designing insurance policies. For example, if efficient moral hazard dominates for a particular service, then cost sharing for treatment of certain serious and life-threatening illnesses provided in this service's facilities might not be desirable. The cost sharing would require the consumer to bear risk; however, it would not provide any changes in his/her health care purchasing decision.

Health-specific moral hazard effects may also be useful to examine the relationship between insurance status and health outcomes. For instance, if additional health care used by the insured for a particular service is higher for worse health states, it could be that less care is associated with worse health outcomes for this service. In this case, the additional health care used by the insured compared with the uninsured is worth the resources spent in producing it. In other words, for consumers in bad health states moral hazard may be reasonable. Such information can be used to make decisions regarding the allocation of resources and the design of policies for the uninsured.

The endogeneity of health insurance complicates the estimation of the relationship between insurance and health care use. Consumers who enter a health insurance contract are not selected at random. Characteristics, such as health, may influence the decision to enter a contract and thus create a self-selection bias. If these characteristics can be hidden prior to the contract, the resulting policy may adversely affect the uninformed parties in the contract. This phenomenon is known as "adverse selection." In addition, insurance companies may attempt to control health care use of high-risk consumers, a procedure known as "screening" or "selection." Either selection bias, adverse selection, or screening potentially confounds the estimation of the moral hazard effect. However, adverse selection upwardly biases effect estimates, while screening downwardly biases these estimates, if left uncontrolled. Recognizing these potential biases, I apply an estimation technique that controls for the nonrandom distribution of insurance, incorporates the selectivity into insurance regime, and takes into account the discreteness and the nonnegativity of the use of health care. Using data from the Household Component of the 2000 Medical Expenditure Panel Survey and its Medical Conditions supplement (Agency for Health Care Research and Quality 2000), I estimate an endogenous switching model for count data, also known as a type-5 tobit model.

I proceed as follows: Section 2 discusses the interdependence of health care and health insurance choices and briefly reviews the literature on moral hazard effects. It also contains a discussion on how the relationship between the moral hazard effect and health may differ across health care services. Section 3 delineates the econometric methodology. Section 4 provides the working definition of health and describes the health care service counts. Section 5 presents the empirical results. Section 6 provides some policy implications and concludes. Sensitivity analysis is provided in the Appendix.

2. Health Insurance, Incentives, and Moral Hazard Effects

Consider an individual consumer who faces a one-period two-date planning horizon. At time zero, the consumer has some exogenous income. He/she knows his/her current health state and chooses his/her health insurance policy using some portion of his/her income. At the time the insurance policy is chosen, time one (that is, future) health state is unknown. At the beginning of time one, the consumer learns his/her new health state and applies his/her remaining income toward the purchase of consumption goods and health care. This is a model of consumer behavior relevant to *interdependent* decisions about health insurance and health care.[2] On the one hand, demand for health care is affected by the insurance policy of the consumer. On the other hand, the choice of health insurance plan could be affected by demand considerations, in particular by planned health expenditure and expectations about health care use. This model motivates the moral hazard effect of health insurance and provides a setting for the estimation of the interdependent demands for health insurance and health care.[3]

A health insurance policy is a contract between an insurer and an individual. Within the duration of this contract, the individual agrees to exchange income in the form of a premium for lower prices for certain health care services in the event of poor health. After signing the contract, the insurer cannot observe the occurrence of poor health. Under this circumstance, the individual has an incentive to report worse health than actual, independent of the random event. This implies that an individual who has experienced a shock to his/her health may spend more resources on health care by overreporting the severity of the shock. In other words, because of the difficulty of specifying whether a loss has occurred, the size of the loss is affected by health insurance. This effect of insurance on the demand for health care is known as the *ex post moral hazard effect,*[4] which is often described as the price effect of insurance on the demand for health care: An insured individual may spend more resources on health care, since insurance decreases the effective price of health care (Arrow 1963; Pauly 1968; Zweifel and Manning 2000).[5] Indeed, the model discussed above suggests that if health care is a noninferior good, then health care demand is decreasing in the fraction of health care costs paid out-of-pocket. When a consumer purchases more generous insurance coverage, the fraction decreases, causing an increase in the use of health care.

The ex post moral hazard effect and attempts to deal with it have been a central focus of many studies of the demand for health care. Pauly (1968) shows that the effect of moral hazard can cause insurance among some types of uncertain events to be nonoptimal even if all individuals are risk averters. Many studies document the existence of the ex post moral hazard effect by estimating the change in the consumer's health care demand in response to changes in the characteristics or

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[2] The interdependence between insurance demand and health care use has been noted. See, for example, Cameron et al. (1988), Nyman (1999b), Cutler and Zeckhauser (2000), and Zweifel and Manning (2000).

[3] For a formal description of this model see Cameron et al. (1988) and Koç (2004).

[4] Health insurance is differentiated from other types of insurance by incorporating this type of moral hazard effect, which, as Pauly (2000) mentions, by an order of magnitude, is unique to health insurance. This is achieved by the form of insurance benefits: a subsidy for the purchase of health care. However, Nyman (2003) argues that individuals demand health insurance because they desire an income transfer from the healthy if they were to become ill. The theory of Nyman (2003) suggests that even if the insurance contract is paid off by decreasing the price of health care, a contingent claims payoff is incorporated into the price subsidy.

[5] Insurance may also give the individual an incentive to decrease the level of preventive activity because changes in preventive activity, even though they affect the individual's expenditure for health care, do not affect the insurance premium. In other words, through his/her preventive activity, the individual may have an effect on the probability of the occurrence of poor health. This effect of insurance on the demand for health care is known as the *ex ante moral hazard effect* (Ehrlich and Becker 1972). This paper takes the probability of the occurrence of poor health as exogenous and focuses on ex post moral hazard effect.

parameters of the insurance contract. Newhouse et al. (1980) estimate the response to a change in deductible; Beck (1974), Cherkin, Grothaus, and Wagner (1989), Harris, Stergachis, and Ried (1990), and Hughes and McGuire (1995) to a change in dollar copayment; Scitovsky and Snyder (1972), Manning et al. (1987), and Keeler and Rolph (1988) to a change in coinsurance rate. Others document the existence of the ex post moral hazard effect by estimating the difference in health care use between the insured and uninsured (e.g., Cameron et al. 1988; Coulson et al. 1995).[6] Other studies, arguing that moral hazard creates a wedge between the cost of health care and its price, estimate the welfare loss from excessive health insurance (Pauly 1968; Feldstein 1973; Feldman and Dowd 1991; Manning and Marquis 1996). In an attempt to reduce the welfare loss created by the moral hazard effect of insurance, this line of work recommends demand-side policies such as raising coinsurance rates and deductibles. However, Nyman (1999a, 2003), showing that a contingent claims payoff is incorporated into the price subsidy provided by health insurance, demonstrates that the conventional moral hazard effect includes both inefficient and efficient health care use, and thus the welfare implications of health insurance are ambiguous.

This paper seeks to expand the existing literature on the welfare implications of health insurance by analyzing health-specific moral hazard effects. It is important to note that since health care services are inputs to health production, the effect of insurance on the demand for health care depends on the marginal utility of health. Given that marginal utility of health is highly related to the consumer's initial health, the moral hazard effect of insurance likely varies by health. This is evidenced by the findings of the clinical literature that concludes that ill consumers use more health care services when insured.[7] Consequently, as Nyman (2003) suggests, each health state may have its own moral hazard profile.

Health insurance may affect the demand for health care services with varying intensity, and thus each health state may have different moral hazard profiles across different health care services. Health care services differ in characteristics such as price elasticity, risk of mortality, cost, and probability of occurrence. For example, the severity of services that require hospitalization is greater than that of services requiring an office visit with a physician because of increased probability of mortality and increased recuperation time required. Furthermore, the demand for such services is likely to be relatively price inelastic (assuming the individual has the income to pay for these services at all prices), since they may include medical procedures that have high intrinsic value in terms of their impact on mortality. This suggests that nonpecuniary costs are high for inpatient services, and thus the additional health care used may be due to an illness occurring and may not be discretionary. For some of physician services, however, the additional health care may be discretionary in the sense that it could be beneficial to consumers regardless of their health status. Therefore, because inpatient services are less discretionary than outpatient services, one would expect that the moral hazard effect for relatively worse health states would be higher compared with the effects for relatively better health states.

3. Estimation

Three attributes complicate the estimation of the interdependent demands for health insurance and health care. First, insurance is not distributed randomly. It is likely endogenous to the health care

[6] Like these studies, this paper also characterizes the private health insurance coverage with an indicator variable representing the presence of insurance and estimates the moral hazard effect of insurance as the difference between the health care use of the insured and uninsured.

[7] See Brown, Bindman, and Lurie (1998) for an excellent summary.

decision leading to potential biases in the estimation of health care demand if left uncontrolled. Second, the differences in health care use across insurance regimes cannot be addressed with a single parameter. Insurance likely modifies the relationship between the socioeconomic variables and health care use by providing access to an entirely different system of care. Third, use of health care is discrete and nonnegative in the form of a count of services over a period of time. These three attributes give rise to application of an endogenous switching model, also known as a type-5 tobit, for count data that was proposed by Terza (1998).[8] The remainder of this section motivates the choice of the type-5 tobit and provides a brief description of it. The model's formal details appear in Terza (1998).

Let $f(y_j^*|X_j, \varepsilon_j)$, $j = 1, 2$ be the conditional probability density function of the count dependent variables. $y_j^* = 0, 1, 2, \ldots$ are the count dependent variables that represent the number of health care services over a stated period of time for subpopulation j. For the specific application in this paper, y_1^* is the use of health care by the insured and y_2^* is the use of health care by the uninsured. ε_j is the interpersonal heterogeneity[9] component and X_j is a vector of explanatory variables.

Switching variable d is characterized by a latent variable model $d^* = Z\alpha + \xi$ where Z is a vector of exogenous variables determining d^*. It is assumed that only the sign of d^* is observed. Thus, I define

$$d = \begin{cases} 1 & \text{if } Z\alpha + \xi > 0 \\ 0 & \text{otherwise.} \end{cases}$$

d is the outcome of the binary switching variable that represents the presence of private health insurance.

Instead of fully specifying the model by assuming a particular form for $f(y_j^*|X_j, \varepsilon_j)$, it is assumed that the conditional means can be written as

$$E[y_j^*|X_j, \varepsilon_j] = \exp\{X_j'\beta_j + \varepsilon_j\}, \quad \text{for } j = 1, 2,$$

which is a weaker assumption. Note that this conditional mean assumption is satisfied in both the Poisson and negative binomial regression models, which are the benchmark models for count data. The following sample selection rule is followed:

$$y_1 = \begin{cases} y_1^* & \text{if } d^* > 0, \\ 0 & \text{otherwise,} \end{cases} \qquad \text{and} \qquad y_2 = \begin{cases} y_2^* & \text{if } d^* \leq 0, \\ 0 & \text{otherwise.} \end{cases}$$

Finally, it is assumed that $\{\varepsilon_1, \varepsilon_2, \xi\}$ are identically and independently distributed (i.i.d.) drawings from a trivariate normal distribution with mean vector zero and covariance matrix

$$\begin{bmatrix} \sigma_{11}^2 & \sigma_{12} & \sigma_{11}\rho_1 \\ \sigma_{12} & \sigma_{22}^2 & \sigma_{22}\rho_2 \\ \sigma_{11}\rho_1 & \sigma_{22}\rho_2 & 1 \end{bmatrix}.$$

To find the regression functions for the subpopulations, one needs to derive

$$E[y_1|X_1, d = 1] \qquad \text{and} \qquad E[y_2|X_2, d = 0]. \tag{1}$$

[8] This approach can effectively be used for any nonnegative dependent variable since rather than modeling the probabilities of single events, it only specifies the conditional expectation.

[9] ε_j reflects a specification error, such as unobserved omitted exogenous variables from the set X_j.

In this paper's application, these two equations specify the expected use of health care conditional on being insured and uninsured, respectively. Terza (1998) shows that

$$E[y_1|X_1, d = 1] = \exp\{X_1'\beta_1^*\}\frac{\Phi(\theta_1 + Z'\alpha)}{\Phi(Z'\alpha)}, \tag{2}$$

where β_1^* is the same as β_1 except that the first element corresponding to the constant term is multiplied by $\sigma_{11}^2/2$, $\theta_1 = \sigma_{11}\rho_1$, and $\Phi(\cdot)$ denotes the standard normal cumulative distribution function. Similarly,

$$E[y_2|X_2, d = 0] = \exp\{X_2'\beta_2^*\}\frac{1 - \Phi(\theta_2 + Z'\alpha)}{1 - \Phi(Z'\alpha)}, \tag{3}$$

where $\theta_2 = \sigma_{22}\rho_2$ and β_2^* is defined similarly as above.

Given the conditional mean functions in Equations 2 and 3, one can motivate the exponential regression functions,

$$y_j = m_j(X_j, Z, \beta_j^*, \theta_j; \alpha) + e_j \qquad \text{for } j = 1, 2,$$

where $m_j(X_j, Z, \beta_j^*, \theta_j; \alpha)$ is defined in Equation 2 for $j = 1$ and it is defined in Equation 3 for $j = 2$, and e_j is a stochastic error with $E(e_j|X_j, d) = 0$. To estimate the above system, I employ the two-stage method of moments estimation proposed in Terza (1998).[10]

In the first stage, given the binary nature of private insurance status, I apply a probit model. In the second stage, conditioning on first-stage probit estimates, I apply nonlinear least squares. I split the sample into two by insurance status and estimate the use of health care services among the insured and uninsured separately. Within the functional forms, this procedure corrects for the endogeneity of insurance by multiplying the expected demand functions with terms similar to the inverse Mill's ratio (see Eqns. 2 and 3).

As a by-product of the correction term, this estimation procedure yields a parameter θ, indicative of the endogeneity bias. As Coulson et al. (1995) and Terza (1998) point out, the sign and significance of θ corresponds to the correlation between the unobservables in the demand for insurance and those in the demand for health care. If θ is positive and significant, then the unobservables in the use regressions and the unobservables that determine the outcome of the binary private insurance variable are positively correlated, and the data are consistent with *adverse selection.* On the other hand, if θ is negative and significant, then these unobservables are negatively correlated, and the data are consistent with *screening*. Statistical tests on θ are performed to inspect the potential endogeneity of insurance and to assess the type of selectivity.

The type-5 tobit model also addresses the selectivity into insurance regime. Ignoring this selectivity, one might suggest an endogenous treatment model (i.e., a type-3 tobit model) for count data as estimated by Terza (1998),[11] McGeary and French (2000), and Kenkel and Terza (2001) or apply a generalized method of moments (GMM) estimation with the predicted probability of having private insurance from the probit model as an instrument for insurance.[12] Either procedure would control for the potential bias caused by the endogeneity of insurance, and each allows the estimation

[10] As stated in Terza (1998), a heteroskedasticity-consistent estimator is used for the asymptotic covariance matrix of the second-stage estimator.

[11] The methodology of Terza (1998) accommodates both endogenous treatment effects and endogenous regime switching for count data. These papers provide applications for the endogenous treatment effect version of the general formulation of Terza (1998).

[12] Examples of GMM estimation of an endogenous treatment effect model appear in Vera-Hernandez (1999) and Schellhorn (2001).

of the determinants of health care use. However, neither allows for the complete interaction between insurance and the determinants of use. With this approach, I am able to estimate the demand equations for the insured and the uninsured separately and identify differences in use across insurance regimes.

With the parameters from the demand estimations, the health-specific moral hazard effect estimates are computed. I follow the approach of Lee (1978), who estimates the average percentage increment of the wage rate for the union sector compared with the nonunion sector using the parameters from a type-5 tobit model for the continuous-dependent variable case. First, I estimate the expected use with insurance and without insurance for each observation by imputing the values of each observation's explanatory variables in the estimated demand models. I then estimate the percentage moral hazard effect for each consumer. Next, I average the individual effect estimates across a subsample with similar health to estimate the average percentage moral hazard effect for that subsample. This is the average treatment effect of insurance by health subsample, that is, the expected change in health care use as a result of being privately insured for a randomly chosen individual from a given health subsample.

4. The Data

I analyze a sample of 11,518 adults between the ages of 18 and 64, drawn from the Household Component of the 2000 Medical Expenditure Panel Survey (MEPS) and its Medical Conditions supplement that provides information on chronic and serious health conditions (Agency for Health Care Research and Quality 2000). MEPS is cosponsored by the Agency for Health Care Policy and Research, and National Center for Health Statistics. It is a nationally representative survey of the U.S. population that provides data on demographics, health status, use of health care services, health insurance coverage, income, and employment. The survey is designed as an overlapping panel so that individuals are interviewed five times covering two calendar years and each year a new panel is started. In this paper, I use information collected in 2000.

I start with a data set of 25,096 individual records. Family income and family-level health status variables are constructed before the deletion of elderly and individuals younger than 18. I removed 9983 individuals who are either elderly or children under 18 from the data set. I removed 1242 observations containing veterans and individuals who are covered by Champus/Champva insurance since their health care demand and access to health care distinctly differs from the general population. I removed 2332 additional observations from the data set due to incomplete responses or due to being designated as nonkey and out of scope,[13] and I removed another 21 because of inconsistent responses.

Following Cameron et al. (1988) and Vera-Hernandez (1999), I apply a practical definition of health based on definitions of disease, illness, and disability. For each of these three dimensions of health, I construct a criterion for a binary indicator. Disease, the state when something has objectively and demonstratively gone wrong in the mechanism of an organism, is identified by the existence of chronic or serious health conditions during the year.[14] Illness, the mental state that is known to follow

[13] An individual is considered as in-scope during a round of interviews if he/she is a member of the U.S. civilian, noninstitutionalized population during that round. An individual is *key* if he/she is linked to the set of National Health Interview Survey sampled households designated for inclusion in MEPS. Only individuals who are in-scope, key, and responded for the full period in which they are in-scope are assigned positive personal weights by MEPS.

[14] Disease indicates whether the person has one of the following conditions during the year: long-term life-threatening conditions such as cancer, diabetes, emphysema, high cholesterol, human immunodeficiency virus/acquired immunodeficiency syndrome (HIV/AIDS), hypertension, ischemic heart disease, and stroke; chronic manageable conditions such as arthritis, asthma, gall bladder disease, stomach ulcers, and back problem of any kind; and Alzheimer's disease or other dementias, depression, and anxiety disorders.

physical and psychological disorders, is inherently subjective. The usage of "Poor" and "Fair" responses in the self-reported health index as the indicator of illness allows for this subjectivity. A variable is created that indicates whether the individual was in poor or fair health at some time during the year. Disability, the final component of health, is the loss of opportunity imposed by social and environmental factors on people with impairments relative to a perceived norm of hindrance. I recognize the presence of disability based on functional limitation status and use a variable that indicates whether the individual had a functional limitation at any time during the year.[15] Disability addresses the effect that a disease has on an individual as a whole. Some disease may create a functional limitation and some may not. According to these definitions, disability is a subset of disease since impairment is necessary for disability and disease is necessary for impairment. The combination of these three indicators separates the sample into six disjoint health groups, H1–H6. The creation of these disjoint sets removes concerns about multicollinearity between disease, illness, and disability variables and allows the construction of health paths. The definitions of all regressors along with the definitions of dependent variables are reported in Table 1.

I construct two health paths, path 1 and path 2, from worst to best health. An individual in the worst health, H1, is ill, disabled, and has at least one chronic or serious disease. However, an individual in the best health, H6, is neither ill, nor disabled, nor has any chronic or serious diseases. If an individual were gradually transformed from H1 to H6 according to path 1, that is, H1, H2, H5, then H6, he/she would first lose his/her illness, then disability, followed by disease. Similarly, path 2, that is, H1, H3, H4, then H6, first decreases in disability, then disease, followed by illness.

An individual who has obtained his/her insurance through employment may have chosen to be insured in order to provide health insurance for a family member, for example, a child.[16] Alternatively, the fact that another member's poor health makes it worthwhile to purchase private insurance for this family member reduces the marginal cost of insurance for the individual, since employers typically subsidize the cost for dependents. Thus, it is important to consider the health of all family members as determinants of insurance. In an attempt to reach this goal, I construct family-level health variables FH1–FH6 similar to individual-level health variables H1–H6.[17] For example, FH1 takes the value 1 if the individual or anyone in the family is ill, disabled, and has at least one chronic or serious disease.[18]

Explanatory variables relevant to the individual's ability to purchase health insurance are family income and employment variables. Certain characteristics of an individual's employment[19] are

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[15] This is a combined measure that indicates whether the individual has one or more of the following limitations:

(i) Needs help with instrumental activities of daily living such as doing laundry or taking medications
(ii) Needs help with activities of daily living such as bathing or dressing
(iii) Difficulty in performing certain physical actions such as walking, lifting, or climbing stairs
(iv) Limitations in work, housework, or school
(v) Cognitive limitations such as confusion or memory loss
(vi) Sensory limitations such as visual or hearing impairments

[16] In this paper, a family is defined as a health insurance eligibility unit, which includes adults plus those family members who would typically be eligible for coverage under the adults' private health insurance family plans. Health insurance eligibility units include adults, their spouses, and their unmarried natural/adoptive children age 18 and under. Children under 24 who are full time students are also included.

[17] Blumberg, Nichols, and Banthin (2001) also use family-level health status variables as determinants of health insurance.

[18] Using individual-level health status variables instead of family-level health variables in the probit regression for private health insurance does not change any of the results reported in this paper, including the results of the sensitivity analysis reported in the Appendix.

[19] An individual is considered to be employed if he/she holds a current main job at the time of the interview or if he/she has such a job to which to return.

Table 1. Definitions of Variables

Variable	Description of Variable	Mean	Standard Deviation
H1	1 if disease, illness, and disable	0.09	0.29
H2	1 if disease, disable, and no illness	0.08	0.27
H3	1 if disease, illness, and no disable	0.06	0.24
H4	1 if illness, no disease, and no disable	0.05	0.21
H5	1 if disease, no illness, and no disable	0.21	0.41
H6	1 if no disease, no illness, and no disable	0.51	0.50
Family-Level Health Status Variables: 1 if anyone in the family has			
FH1	Disease, illness, and disable	0.14	0.35
FH2	Disease, disable, and no illness	0.10	0.31
FH3	Disease, illness, and no disable	0.10	0.30
FH4	Illness, no disease, and no disable	0.05	0.21
FH5	Disease, no illness, and no disable	0.26	0.44
FH6	No disease, no illness, and no disable	0.35	0.48
empl	1 if employed	0.74	0.44
self-empl	1 if self-employed	0.09	0.28
union	1 if the individual belongs to a union	0.08	0.27
govm	1 if the company is governmental	0.11	0.31
numempl	Size of workplace in terms of number of employees	103.14	167.42
privins	1 if privately insured	0.72	0.45
pubins	1 publicly insured	0.09	0.29
sex	1 if male	0.42	0.49
age	Number of years old	38.31	12.36
age2	Age squared divided by 1000	1.66	0.99
white	1 if white	0.82	0.39
mar	1 if married	0.58	0.49
univ	1 if at least high school graduate	0.44	0.50
rgn1	1 if resides in the Northeast	0.16	0.36
rgn2	1 if resides in the Midwest	0.21	0.41
rgn3	1 if resides in the South	0.38	0.49
rgn4	1 if resides in the West	0.25	0.43
msa	1 if the individual lives in an urban area	0.78	0.41
inc	Family income divided by 1000	47.09	41.21
opmd	Number of office based visits with a medical physician over the last year	2.96	5.14
ipadm	Number of hospital admissions over the last year	0.09	0.37
ipngt	Number of nights in a hospital over the last year	0.33	1.91

associated with the availability of coverage at the workplace, and thus with the likelihood that an individual and his/her family obtain health insurance. These are the size of the company where the individual works (in terms of number of employees), whether the individual is employed by the federal government, whether the individual belongs to a labor union, and whether the individual is self-employed at his/her current job.

The most important explanatory variable relevant to the individual's ability to pay for health care services is whether the individual has private or public insurance. If an individual has insurance that provides coverage for hospital and physician services at any time during the year (other than Medicare, Medicaid, Tricare, or other public hospital/physician coverage), then he/she is classified as having private insurance. An individual is considered to have public coverage *only* if he/she is not covered by private insurance at any time during the year and if he/she is covered by Medicare, Medicaid, or other public hospital/physician coverage at any time during the year. An individual is defined as uninsured if he/she is not covered by Medicare, Medicaid, Tricare, other public hospital/physician insurance, or private hospital/physician insurance at any time during the year.

The use of two forms of health care services is examined: outpatient and inpatient visits over the last year. The outpatient visit considered is the number of office based visits to a medical physician (opmd), which includes only in-person consultations with a medical doctor and excludes non–physician visits such as chiropractors, nurses and nurse practitioners, optometrists, physician's assistants, psychologists, and physical or occupational therapists. Two types of inpatient visits are considered: total number of hospital admissions[20] (ipadm), which includes hospital stays where the dates of admission and discharge are reported as identical (that is, "zero-night stays"),[21] and the number of non–zero-night stays in the hospital associated with these discharges (ipngt).

5. Results

Probability of Having Private Health Insurance

To estimate the endogenous switching model, I estimate a probit model on the presence of private health insurance, which also allows me to evaluate the determinants of insurance demand. The results of this regression appear in Table 2. In a nonlinear simultaneous model, identification can in theory be secured by nonlinearity of the functional forms (McManus 1992). However, as suggested by Heckman (2000), exclusion restrictions, that is, variables that affect the endogenous variables but not the relationship, assure more robust identification of the parameters of the relationship. Therefore, the choice of private health insurance (i.e., the selection equation) is identified by a combination of using variables that are independent of health care use and the nonlinearity in functional form between the probit and the count model of health care use. I use job characteristics such as whether the individual is self-employed, whether the individual belongs to a labor union, whether the company the individual works for is governmental, and size of workplace in terms of number of employees as variables that influence the decision to purchase private health insurance but do not directly affect health care use (Johnson and Crystal 2000; Munkin and Trivedi 2003). I also use the region in which the individual resides as a further identifying variable (Cameron et al. 1988).

The causal interpretation of an empirical relationship in a simultaneous model relies on the validity and strength of the identifying assumptions. Examining the results of the first-stage probit regression reveals that the identifying variables are highly significant. As discussed below, the marginal effects of self-employment, unionization, and employment status on the probability of having private insurance are very high compared with the marginal effects of demographic characteristics and health status variables. In addition, the predictive power of the probit regression is considerably high. The pseudo R^2 is 0.32, and the percentage of observations correctly predicted is 81.55.[22] The majority of the explanatory variables are statistically significant at the 1% level. These

[20] The total number of hospital discharges is actually reported in the data.

[21] These zero-night stays can include surgical operations as well as other kinds of treatment. Excluding zero-night stays from the definition of admissions does not change the results reported in this paper.

[22] According to this measure, if the actual value of private insurance for an observation is 1 and the corresponding predicted probability of having private health insurance from the probit regression is $\geq$0.5, this observation is counted as correctly predicted. Similarly, if the actual value of private insurance is 0 and the corresponding predicted probability is $<$0.5, the observation is also counted as correctly predicted.

Table 2. Probit Regression for Private Insurance

Variable	Coefficient	*z* statistic	Marginal Effects
sex	−0.107	−3.45*	−0.027
age	−0.049	−6.24*	−0.012
age2	0.650	6.63*	0.164
white	0.150	3.93*	0.039
mar	0.305	8.78*	0.078
rgn2	0.189	3.48*	0.045
rgn3	−0.045	−0.95	−0.011
rgn4	−0.233	−4.73*	−0.062
msa	0.053	1.47	0.013
univ	0.470	14.02*	0.115
FH1	−0.293	−6.11*	−0.081
FH2	0.024	0.44	0.006
FH3	−0.168	−3.19*	−0.045
FH4	−0.292	−4.30*	−0.083
FH5	0.144	3.42*	0.035
inc	0.017	26.31*	0.004
numempl	0.001	11.87*	0.0003
empl	0.516	13.58*	0.145
self-empl	−0.609	−11.17*	−0.188
union	0.768	7.70*	0.137
govm	0.299	4.39*	0.067
constant	−0.049	−0.33	NA[a]
L	−4561.90[b]		

$N = 11{,}518$. The percentage of observations correctly predicted is 81.55. The pseudo R^2 is 0.32.
[a] NA, not applicable.
[b] *L* is the log likelihood of the probit regression.
* Statistical significance at 1%.

indicate that the first-stage explanatory variables explain the variation in the decision to obtain private health insurance effectively. In sum, these results suggest that the predictive power of the first stage and the significance of identifying variables are reliable to a reasonable degree in estimating the effect of private insurance on the demand for health care.

The probit regression results suggest that demographic characteristics have relatively small marginal effects on the demand for health insurance as compared with variables representing health, employment, and access to group coverage. Only education and marital status have marginal effects comparable with those for variables representing health and employment. Being a high school graduate and having some education beyond high school increases the likelihood of having private insurance by about 12%. Married individuals are more likely than unmarried individuals to obtain private insurance. The marginal effect of marital status on the probability of having private insurance is 7.8%. White and female Americans are more likely than nonwhite and male Americans to be covered by private health insurance.

Employment increases the demand for insurance by decreasing premiums.[23] Indeed, being employed increases the predicted probability of private insurance by 14.5%. Federal tax incentives motivate employers to subsidize insurance premiums of their employees. Certain characteristics of an individual's employment are associated with the likelihood that he/she will obtain private health

[23] Obtaining health insurance through place of employment signifies access to group insurance. Access to group insurance decreases insurance premiums because of the vast economies of scale in the insurance industry.

insurance. As the size of the workplace (in terms of number of employees) increases, individuals are more likely to be covered by private health insurance. Being employed in the government increases the predicted probability of private insurance by about 7%. Thus, if an individual is employed by the government, his/her likelihood of obtaining private insurance further increases. The public sector has historically provided more generous employee benefits, which may explain this finding. Union members of employed individuals are more likely to be covered by private insurance. Being self-employed decreases the predicted probability of obtaining private insurance. The fact that the self-employed cannot fully deduct health insurance premiums as a business expense may explain this difference.[24]

Higher income significantly increases the demand for insurance. Individuals with high income may purchase health insurance to protect their assets from health-induced expenditure shocks. These results are consistent with those of earlier studies. Cameron et al. (1988) find that income is an important determinant of the health insurance decision, and Vera-Hernandez (1999) finds that income and employment status are very important in determining health insurance choice.

Under the hypothesis of health-related adverse selection, individuals who anticipate poor health either for them or for a family member are more likely to purchase private insurance because of the corresponding increase in the expectation of health care use. The probit results cast doubt on the existence of adverse selection for observable variables. For example, being in the worst health state (FH1) decreases the predicted probability of private insurance by 8.1% compared with being in the state of perfect health (FH6). Similarly, being in the health states FH3 and FH4 decreases the predicted probability of private insurance by 4.5% and 8.3%, respectively, compared with being in the state of perfect health. As to the remaining two health status variables, their coefficient estimates are positive, but only that of FH5 is significant and suggests that having a disease but no illness and functional limitations increases the predicted probability of private insurance by 3.5% relative to being in the state of perfect health. Nevertheless, these estimated coefficients suggest that the structure of the private health insurance industry may favor the healthy.

The Demand for Health Care Services by Insurance Status

In addition to these insurance demand results, I also obtain an estimate for the correlation between the unobservable determinants of insurance and health care demands, θ, as part of the estimation of health care service demands. As Coulson et al. (1995) and Terza (1998) point out, this correlation not only allows one to test the endogeneity of insurance, it also provides evidence as to the type of selection. According to the results (Table 3), θ is significantly negative in the demand for physician visits and hospital nights among the insured. These results are consistent with screening or selection in the demand for these services. They are also consistent with the health-related adverse selection results discussed above. All other θ estimates are insignificantly negative, except one; the correlation in the uninsured's demand for physician visits is insignificantly positive.

This evidence of screening in the self-selection results may reflect the structure of the U.S. health care industry. Most privately insured individuals obtain their insurance coverage through employment or that of a family member; employment and insurance are bundled goods. Employees who choose the same health plan usually pay the same premium and are subject to the same other requirements. Therefore, insurance companies do not charge premiums based on individually rated expected cost. Instead, insurers may have a financial incentive to control the use of health care services. For example, they could offer incentives to gatekeeper physicians not to refer patients to specialists. They may let

[24] They are now allowed to fully deduct the costs of their insurance premiums as a business expense.

Table 3. Two-Stage Method of Moments Estimation of Health Care Demand[a]

	Physician Visits		Hospital Nights		Hospital Admissions	
Variable	Insured	Uninsured	Insured	Uninsured	Insured	Uninsured
msa	0.009	0.020	−0.464	0.739	−0.317	0.187
	(0.19)	(0.23)	(−1.86)	(2.79)*	(−1.78)	(1.16)
age	0.007	0.038	0.128	−0.049	0.008	−0.008
	(0.61)	(1.71)	(1.96)**	(−0.74)	(0.21)	(−0.23)
age2	−0.038	−0.341	−1.917	0.646	−0.163	0.041
	(−0.26)	(−1.25)	(−2.46)*	(0.77)	(−0.31)	(0.08)
sex	−0.373	−0.393	1.212	0.244	0.162	−0.319
	(−8.49)*	(−4.61)*	(4.52)*	(0.74)	(0.93)	(−1.65)
white	0.156	0.177	0.009	−0.013	0.210	0.060
	(2.64)*	(1.95)**	(0.02)	(−0.04)	(1.22)	(0.36)
mar	0.055	−0.112	−0.684	0.452	0.217	0.233
	(1.07)	(−1.22)	(−2.09)**	(1.55)	(0.90)	(1.28)
univ	0.077	0.149	−1.417	−0.413	−0.074	−0.156
	(1.59)	(1.30)	(−3.99)*	(−1.18)	(−0.35)	(−0.66)
empl	−0.208	−0.187	−1.801	0.770	−0.502	0.262
	(−3.48)*	(−1.50)	(−3.87)*	(1.69)	(−1.95)**	(1.03)
inc	0.0006	0.006	−0.035	−0.037	−0.008	−0.011
	(0.91)	(3.73)*	(−4.08)*	(−1.76)	(−2.01)**	(−1.60)
H1	1.495	1.478	4.156	2.443	2.078	1.354
	(24.55)*	(13.03)*	(13.2)*	(7.58)*	(9.98)*	(6.36)*
H2	0.859	0.789	1.334	1.140	0.963	0.328
	(13.97)*	(6.58)*	(3.48)*	(2.65)*	(5.79)*	(1.04)
H3	1.097	1.179	2.657	1.664	1.524	1.026
	(16.61)*	(9.48)*	(5.33)*	(4.72)*	(8.49)*	(4.28)*
H4	0.591	0.363	1.671	1.248	1.179	0.373
	(5.87)*	(2.53)*	(3.69)*	(1.90)**	(5.29)*	(1.18)
H5	0.620	0.824	0.871	1.156	0.429	0.722
	(13.78)*	(7.75)*	(2.94)*	(3.38)*	(3.23)*	(3.51)*
pubins		0.590		1.110		1.084
		(6.20)*		(3.32)*		(5.81)*
constant	0.527	−0.977	−0.192	−2.514	−2.221	−3.155
	(2.04)**	(−2.32)*	(−0.13)	(−2.15)*	(−2.69)*	(−4.15)*
θ	−0.216	0.135	−2.038	−0.047	−0.649	−0.154
	(−2.36)*	(0.78)	(−6.52)*	(−0.09)	(−1.50)	(−0.29)

$N = 11{,}518$.
[a] t-statistics in parentheses.
* Statistical significance at 1%.
** Statistical significance at 5%.

their members know who are relatively "expensive" doctors and hospitals. They may also share the risk of patients with contracted providers of care, thereby giving the providers an incentive to control health care use of patients.

The parameter estimates produced by the switching model illustrate the determinants of health care use (Table 3). The non–health-related coefficients portray a complex relationship between the demand for health care services and the insurance state. Males demand fewer physician visits. White individuals demand more physician visits than nonwhites. These results hold across both insurance states, that is, the privately insured and the privately uninsured, which include individuals with public insurance. Employment does not significantly affect the demand for physician visits for the uninsured; however, employed individuals among the insured demand fewer physician visits. The demand for inpatient services among the uninsured is relatively unresponsive to changes in socioeconomic characteristics. Living in an urban area increases the demand for hospital nights; other socioeconomic variables do not have a statistically significant effect on the demand for inpatient services. Among the insured, males demand more hospital nights. Employed individuals demand fewer hospital nights, and the number of hospital admissions is lower for this group of individuals. This is not surprising since employment indicates both some level of health as well as a higher cost (in work time sacrificed) in using health care. The higher educated individuals demand fewer hospital nights. This result is consistent with the hypothesis that schooling, increasing the efficiency of health production, increases the amount of health produced from a given set of health inputs. Consequently, the demand for health care may decrease. Lastly, married individuals demand fewer hospital nights.

Among the insured, the coefficient of income is insignificant for physician visits, whereas it is significantly negative for inpatient services. Individuals with greater family income more likely can afford better housing, home care, and other appealing substitutes to hospital rooms. On the other hand, among the uninsured, the coefficient of income is significantly positive for physician visits, while it is not significant for inpatient services. It is interesting to compare theses results with some previous findings. Cameron et al. (1988) find that the number of admissions decrease with income but otherwise health care service use appears to be income insensitive. Schellhorn (2001) reports that income does not have a significant effect on both specialist and primary physician visits. They model the demand for health care services with an endogenous treatment effect model (that is, modeling the change in insurance regime with an intercept shift); thus, the effect of an independent variable on health care use is the same for both the insured and uninsured. My results suggest that insurance modifies the relationship between the independent variables and health care use. Among the uninsured, public insurance has a large and positive effect on the demand for all services.

Health as a determinant of health care services has the highest significance level for all services. In the demand for physician visits and hospital nights, all health coefficients are significantly positive, independent of the insurance state. In the demand for hospital admissions, all health coefficients are significantly positive among the insured. Among the uninsured, the coefficients for H2 and H4 are not significant; the remaining health coefficients are significantly positive. These results are generally consistent with those of Cameron et al. (1988) who report that the health status measures are statistically much more significant in explaining health care use than socioeconomic characteristics.

Health-Specific Moral Hazard Effects

Hospital care is generally provided for diseases that are considered much more serious than those treated in a physician visit. Consequently, I assume that physician services somewhat represent quality of life and hospital services somewhat represent mortality. At all levels of health, individuals may be more concerned with mortality, which may explain the higher moral hazard effects for inpatient services than outpatient services (Table 4).

By comparing the health-specific moral hazard effects across the two health paths, two patterns are revealed. First, for physician visits and for each health path, the health-specific moral hazard effects are generally higher for relatively better health states. For example, for health path 1, the moral hazard effect for the state of perfect health (H6) is higher than those for other health states. In fact, other than the moral hazard effect for H5, all other health states in this path have higher moral hazard effects than the effect for the state of worst health (H1). For health path 2, the moral hazard effect for H6 is higher than those for other health states except that for H4. The moral hazard effect for H4,

Table 4. Health-Specific Moral Hazard Effects

	Physician Visits (%)	Hospital Nights (%)	Hospital Admissions (%)
Health Path 1			
H1	19.2	165.8	57.9
H2	22.4	70.9	58.5
H5	10.5	35.7	17.7
H6	22.6	65	31.03
Health Path 2			
H1	19.2	165.8	57.9
H3	18.8	109.3	48.1
H4	34.9	93.6	61.5
H6	22.6	65	31.03

however, is higher than that for the state of worst health. Thus, these results suggest that in the demand for outpatient services, the moral hazard effect is higher at higher levels of health.

The second pattern appears in the demand for inpatient services. For both hospital nights and hospital admissions and for each health path, the health-specific moral hazard effects are generally lower for relatively better health states. For example, for health path 2, the moral hazard effect for H6 is lower than those for all other health states. For hospital nights, the moral hazard effect for H1 is higher than those for all other health states. For hospital admissions, except for the effect for H4, the moral hazard effect for H1 is also higher than those for other health states. For health path 1, for both hospital nights and hospital admissions, the moral hazard effect for H6 is lower than those for other health states except for the effect for H5. For hospital nights, the moral hazard effect for H1 is higher than the moral hazard effect of all other states. For hospital admissions, the moral hazard effect for H1 is also higher than those for H5 and H6. Thus, these results indicate that in the demand for inpatient services, the moral hazard effect is lower at higher levels of health.[25]

These results should be interpreted in light of service characteristics discussed earlier in the paper. Nonpecuniary costs are high for inpatient services, and thus the additional health care used may not be discretionary since only those with the disease would benefit from it. For many physician services, however, the additional health care may be discretionary since it could be beneficial to consumers at all levels of health. These may explain why the moral hazard effect is lower for relatively better health states for inpatient services and why it is higher for relatively better health states for outpatient services.

6. Discussion

Because health insurance creates a gap between the cost of health care and its price, the additional health care services used by insured consumers are considered to be inefficient. However, the results of the clinical literature suggest that for health care services that have high intrinsic value in terms of their impact on mortality, some portion of moral hazard may in fact be the intended result of purchasing health insurance instead of an opportunistic response to a price subsidy. This literature

[25] As mentioned in the data description, hospital admissions include hospital stays where the date of admission and discharge are identical (that is, zero-night stays). These zero-night stays can include surgical operations as well as other kinds of treatment. Excluding them from the definition of admissions does not change the results. The moral hazard effect for H1 becomes 66.35%. The moral hazard effects for the remaining health states do not change significantly. Under this definition of admissions, the moral hazard effect for H1 is higher than the moral hazard effects for all other health states.

argues that for individuals in bad health states moral hazard spending is often life saving. Therefore, the additional health care used by the insured compared with the uninsured is worth the resources spent in producing it.

Nyman (2003) formalizes this view by arguing that individuals demand health insurance because they desire an income transfer from the healthy in the event of poor health. His theory suggests that even though a price subsidy is used to pay off the health insurance contract, this subsidy incorporates an income transfer from the healthy to the ill. In other words, a contingent claims payoff is incorporated into the price subsidy provided by health insurance. Since this additional income may lead to additional use of health care services, income transfers may cause a portion of the conventional moral hazard effect. However, this portion is efficient because its value, that is, the willingness to pay for health care, exceeds its costs, that is, the marginal cost of producing health care. This is because becoming insured increases the willingness to pay for health care for every unit of care. This is a major difference between the theory of Nyman (2003) and the conventional theory, which assumes that the individual moves along his/her demand curve even after he/she becomes insured. With this new theory, Nyman (2003) demonstrates that moral hazard is composed of both an efficient portion generated by income transfers and an inefficient portion generated by opportunistic responses to price subsidies. The inefficient moral hazard is an opportunistic response by the healthy person. He/she can substitute consumer-oriented health care for other consumer goods and services as the prices change (that is, cosmetic surgery). The efficient moral hazard is the intended response of the ill individual who buys insurance so that in the event of poor health, he/she will be able to purchase more care than without insurance by using the income transferred from those who remain healthy.

The empirical results in this paper suggest that additional outpatient services used by insured consumers are higher for relatively better health states and additional inpatient services used by the insured are higher for relatively worse health states. In light of the above discussion, these results suggest that for inpatient services the additional health care used by the insured may be the intended result of purchasing insurance. For outpatient services, however, it may be the opportunistic response to a price subsidy. Thus, both efficient and inefficient moral hazard may exist, and this may depend on the type of health care service used. As mentioned above, the moral hazard effect regarding the physician services may be interpreted as the quality of life effect, and the moral hazard effect regarding the hospital services may be interpreted as mortality. In light of the theory of Nyman (2003), my results suggest that for the seriously ill efficient moral hazard may dominate because the income transfer effect is large and the price effect is small. For quality of life enhancing procedures, however, the inefficient moral hazard may dominate, since the income transfer effect is small and the price effect could be large.

Nyman (2003) argues that optimal health insurance should be designed such that different cost-sharing rules are applied to different diseases with different moral hazard profiles. For those illnesses where efficient moral hazard dominates, cost sharing should not apply. These might be illnesses that are life threatening and expensive to treat. For those illnesses where inefficient moral hazard dominates, however, cost sharing should be imposed. These might be diseases that are less serious or less expensive to treat. Chernew, Encinosa, and Hirth (2000) model such a health insurance policy design. Their insurance design suggests that for serious illnesses, the optimal policy would be for the insurer to pay the consumer if the consumer chooses the medically appropriate but the least expensive treatment path.[26]

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[26] Chernew, Encinosa, and Hirth (2000) argue that for each disease state there is some minimum amount of health care expenditures spent by consumers that correspond to medically appropriate but least expensive treatment path. In other words, there is a nondiscretionary amount of health care use. It is not optimal to apply any cost sharing to this portion of use, since cost sharing would make the consumer bear risk without any changes in his/her health care purchasing decision.

However, if a high-cost treatment path is chosen, then the optimal policy would be for the consumer to pay the insurer.

In light of the insurance design of Chernew, Encinosa, and Hirth (2000) and the theory of Nyman (2003), the empirical results in this paper suggest differential cost-sharing rules for treatment of certain illnesses provided in outpatient and inpatient facilities. Since it appears that efficient moral hazard dominates for inpatient services, cost sharing could be minimal for treatment of serious and life-threatening illnesses provided in an inpatient facility. On the other hand, since inefficient moral hazard appears to dominate for outpatient services, some cost sharing could be imposed for the treatment of less serious illnesses provided in an outpatient facility.

The empirical results may suggest a different story for insurance companies, since they not only worry about the use behavior of their clients, such as the moral hazard effect, but also their expected health. Insurance companies could increase the cost sharing of procedures and treatment methods for individuals with serious health conditions provided in an inpatient facility and the cost sharing of those procedures for the relatively healthy provided in an outpatient facility. Since the latter would likely adversely affect their risk pool, the former is more likely instated to the dismay of those who need such inpatient care. This is not a desirable outcome when one recognizes that moral hazard has both an inefficient component and an efficient component. Thus, the financial incentives of these companies may not match the preferences of the public. If the policy makers choose not to intervene, the dynamics of this trade-off may lead insurance companies to effectively reduce coverage for certain inpatient care.

Appendix: Sensitivity Analysis

In the endogenous switching model estimated in this paper there are two regimes of health care demand. The first is the regime for the privately insured, and the second is the regime for the privately uninsured, which includes individuals with public insurance. In the demand for health care services among the privately uninsured, the effect of public insurance on use is accounted for by an indicator variable. However, since the publicly insured have use patterns similar to those of the privately insured (Weissman and Epstein 1993), it can be argued that publicly insured may belong to the health care regime of the privately insured. This raises the issue whether the existing demand equations for the privately insured and the uninsured actually represent that or some other concept such as high and low income, since the uninsured and publicly insured are generally low-income individuals. As discussed below, interpretation of the coefficients of the determinants of health care demand for the insured may be misleading if one combines the privately insured with the publicly insured. Therefore, to test the sensitivity of the coefficient estimates of the determinants of health care demand for the privately insured and uninsured and of the health-specific moral hazard effect results to the definition of the uninsured, publicly insured individuals are removed from the sample[27] rather than combining them with the privately insured, although the sensitivity analysis results are very similar in both ways. Regardless of whether the publicly insured is combined with the privately insured or removed from the sample, the optimization routine for the two-stage method of moments converges only for outpatient services. For inpatient services, it does not converge for the uninsured. The reason is that there are very few individuals with nonzero use for inpatient services among the uninsured without the publicly insured.[28] I am therefore able to provide robustness results for physician visits only.

There are several reasons for combining the uninsured and the publicly insured in the same health care regime separate from that of the privately insured. First, the demographic characteristics of the two groups are similar. For example, nearly two-thirds of the uninsured are low-income individuals or from low-income families (The Kaiser Commission on Medicaid

[27] Removing the publicly insured from the sample does not materially change the means and standard deviations of the variables except for employment status, private insurance status, worst health status (H1), office-based physician visits, and nights in the hospital. The mean of employment status increases from 0.74 to 0.79. The mean of private health insurance coverage increases from 0.72 to 0.79. The mean of H1, however, decreases from 0.09 to 0.06. Similarly, the means of office-based physician visits and hospital nights decrease from 2.96 and 0.33, respectively, to 2.76 and 0.25, respectively.

[28] For physician visits, the percentage of nonzero observations is 68, 50, and 38 for the privately insured, privately uninsured, and uninsured without the publicly insured, respectively. For both hospital admissions and hospital stays, 93% of the privately insured (out of 8290 individuals) and 91% of the privately uninsured (out of 3228 individuals) groups have zero use, whereas for the uninsured without the publicly insured, 96% of the observations (out of 2173 individuals) have zero use.

Table A1. Probit Regression for Private Insurance

Variable	Coefficient	z statistic	Marginal Effects
sex	−0.164	−4.90*	−0.032
age	−0.055	−6.39*	−0.010
age2	0.734	6.72*	0.142
white	0.054	1.27	0.010
mar	0.249	6.59*	0.050
rgn2	0.079	1.28	0.015
rgn3	−0.267	−4.94*	−0.054
rgn4	−0.367	−6.54*	−0.079
msa	0.067	1.76	0.013
univ	0.439	12.24*	0.084
FH1	−0.021	−0.40	−0.004
FH2	0.128	2.14**	0.023
FH3	−0.034	−0.59	−0.006
FH4	−0.230	−3.19*	−0.050
FH5	0.200	4.49*	0.036
inc	0.014	21.70*	0.002
numempl	0.001	11.21*	0.0003
empl	0.343	8.25*	0.075
self-empl	−0.587	−10.53*	−0.147
union	0.717	6.72*	0.096
govm	0.380	5.10*	0.061
constant	0.635	3.80*	NA[a]
L	−3956.51[b]		

$N = 10{,}463$. The percentage of observations correctly predicted is 82.57. The pseudo R^2 is 0.26.
[a] NA, not applicable.
[b] *L* is the log likelihood of the probit regression.
* Statistical significance at 1%.
** Statistical significance at 5%.

and the Uninsured 2003). Since my sample is for adults between the ages of 18 and 64, the majority of the publicly insured obtain it through Medicaid, and Medicaid covers low-income individuals. Second, and more importantly, the health status of the two groups is similar as well. Private insurance covers only a minority of people who are not in good health, and the uninsured are not as healthy as those who have private health insurance. Individuals with public insurance are also not as healthy as those who have private health insurance, since Medicaid covers disabled individuals. Third, these two groups may also be similar in terms of unmet health care needs. For example, Haley and Zuckerman (2000) report that in Texas the percentage of individuals who have unmet health care needs among the uninsured and publicly insured is 25.7% and 23.6%, respectively, whereas only 6.3% of privately insured have unmet health care needs. Fourth, individuals with Medicaid insurance are often limited to the same set of safety-net providers as the uninsured with delays in getting appointments and referrals to specialists and little continuity of care (IOM 2002). For these reasons, interpretation of the coefficients of the determinants of health care demand may be misleading if one combines the privately insured with the publicly insured. Therefore, to carry out the sensitivity analysis discussed above, publicly insured individuals are removed from the sample.

Inspection of Table A1 reveals that the results of the probit regression for private insurance are similar to those in Table 2. There are two differences. First, when the publicly insured are removed from the sample, white individuals are not significantly different from nonwhites in their likelihood of having private insurance. Second, the health-related adverse selection results based on observable variables are inconclusive. Being in health states FH1 and FH3 does not significantly change the likelihood of having private insurance compared with being in the state of perfect health, although the coefficient estimates for both health states are negative. Being in the health state FH4 decreases the predicted probability of private insurance by 5% compared with being in the state of perfect health. However, being in the health states FH2 and FH5 increases the predicted probability of private insurance by 2.3% and 3.6%, respectively, relative to being in the state of perfect health. Thus, these probit results tell a mixed story about the existence of health-related adverse selection, and it would be useful to analyze the sign and significance of θ to reach a conclusion.

This result is not surprising. Since individuals with relatively worse health status are eligible for public insurance (that is, the disabled), health status and probability of having private insurance may be negatively related in the original probit regression because of the inclusion of these individuals in the group of uninsured.

Table A2. Two-Stage Method of Moments Estimation for Physician Visits[a]

Variable	Insured	Uninsured
msa	0.004 (0.09)	−0.407 (−2.14)**
age	0.008 (0.72)	0.104 (2.43)*
age2	−0.058 (−0.40)	−1.119 (−2.11)**
sex	−0.365 (−8.23)*	−0.451 (−2.45)*
white	0.163 (2.73)*	0.197 (0.81)
mar	0.052 (1.01)	−0.154 (−0.77)
univ	0.067 (1.37)	0.742 (3.58)*
empl	−0.210 (−3.66)*	−0.746 (−3.80)*
inc	0.0004 (0.71)	0.006 (2.82)*
H1	1.477 (24.34)*	2.248 (10.84)*
H2	0.852 (13.84)*	1.127 (6.03)*
H3	1.092 (16.61)*	1.110 (5.68)*
H4	0.599 (5.91)*	0.633 (2.94)*
H5	0.614 (13.63)*	1.299 (7.23)*
constant	0.544 (2.08)**	−2.304 (−3.28)*
θ	−0.316 (−3.06)*	0.208 (0.70)

$N = 10{,}463$.
[a] *t*-statistics in parentheses.
* Statistical significance at 1%.
** Statistical significance at 5%.

Table A3. Health-Specific Moral Hazard Effects

	Physician Visits (%)
Health Path 1	
H1	17.4
H2	35.6
H5	17.2
H6	52.3
Health Path 2	
H1	17.4
H3	53.2
H4	56.9
H6	52.3

The parameter estimates produced by the switching model for physician visits appear in Table A2. Overall, the pattern of the results is similar to that in Table 3. θ is significantly negative among the insured. Thus, although the health-related adverse selection results based on observable variables are inconclusive, the correlation between the unobservable determinants of insurance and physician visits demand among the insured is significantly negative, which is consistent with screening in the demand for physician visits.

Health-specific moral hazard effects for physician visits appear in Table A3. For example, for health path 1, the moral hazard effect for the state of perfect health (H6) is higher than those for other health states. For health path 2, the moral hazard effect for the state of worst health (H1) is lower than the moral hazard effect for any other health state. Thus, these results also suggest that in the demand for outpatient services the moral hazard effect is generally higher at higher levels of health.[29]

[29] Including the publicly insured in the group of privately insured does not change these robustness results. The moral hazard effects are remarkably similar. The moral hazard effects, in percentages, for H1 through H6 are 12, 35.8, 54.3, 56.2, 19.4, and 54.5.

Although these qualitative results are remarkably similar to the original results, quantitatively the moral hazard effects are now generally higher. This accords with intuition since, as pointed by Weissman and Epstein (1993), uninsured individuals have fewer physician visits than the privately insured, whereas Medicaid recipients have use patterns as high as the privately insured.

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