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THE VARIATION IN MORAL HAZARD ACROSS CONDITION-SPECIFIC MEDICAL CARE AND HEALTH STATUS

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Abstract

This paper examines whether the magnitude of moral hazard varies by the health status of the individual *and* the type of medical condition associated with the physician office visit. Generalized method of moments is implemented to address the endogeneity of private health insurance, and the nonnegativity and the discreteness of physician services use. The results indicate that the moral hazard effect is higher for the healthy for chronic condition related physician visits, while they do not support an appreciable difference in moral hazard effects between the healthy and sickly groups for acute condition related physician visits. These results suggest that physician care is not a homogenous good and the quantitative characterization of moral hazard in its demand depends on the particular condition-specific component of the visit *and* the health group under consideration.

Key Words: moral hazard, health-specific cost sharing, condition-specific physician visits, count data, GMM estimation

BELİRLİ ŞARTLARA BAĞLI TIBBİ BAKIM İLE SAĞLIK DURUM ARASINDAKİ AHLAKİ TEHLİKEDEKİ DEĞİŞİM

Özet

Bu makale ahlaki tehlikenin büyüklüğünün bireyin sağlık durumuna ve hekim muayenehane ziyareti ile ilişkili tıbbi durumun türüne göre değişip değişmediğini inceler. Genelleştirilmiş momentler yöntemi özel sağlık sigortasının içselliğini, hekim hizmetlerinin negatif olmadığını ve süreksiz olduğunu irdelemek için uygulanmıştır. Sonuçlar akut duruma bağlı hekim ziyaretleri için sağlıklı ve hasta gruplar arasında ahlaki tehlike etkilerinde kayda değer bir farkı desteklemiyorken ahlaki tehlike etkisinin kronik duruma bağlı hekim ziyaretlerinde sağlıklı olanlar için daha yüksek olduğunu gösterir. Bu sonuçlar hekim bakımının homojen bir mal olmadığını ve talepteki ahlaki tehlikenin nicel karakterizasyonunun muayahane ziyaretlerinin özel

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durumlara bağlı olmasına ve incelenmekte olan sağlık gurubuna bağlı olduğunu ortaya koymaktadır.

Anahtar Kelimeler: ahlaki tehlike. Sağlığa özel harcamanın payı, şarta bağlı muayahane ziyareti, sayma verisi, GMM tahmini

INTRODUCTION

The moral hazard effect, which refers to the effect of insurance on the net price of medical care and to the consequent incentive effects on medical care consumption [Arrow (1963), Pauly (1968)], has been a central focus of many studies of the demand for medical care.[1] Most of these studies, however, view medical care as a homogenous good. This paper examines whether the magnitude of moral hazard varies by the health status of the individual *and* the type of medical condition (chronic vs. acute) associated with the physician office visit.

Using the estimated moral hazard effects the paper explores whether optimal cost sharing in health insurance should vary by the medical condition associated with the medical visit *and* the clinical characteristics of the insured. According to the conventional theory of the demand for health insurance, although the risk avoidance aspect of insurance benefits consumers, it also creates a welfare loss, since the moral hazard consumption involves consumption of medical services whose value to the consumer is less than its cost of production [Pauly (1968), Feldstein (1973), Feldman an Dowd (1991), Manning and Marquis (1996)]. Consequently, cost sharing should be imposed to reduce moral hazard welfare losses. The main determinant of optimal cost sharing in the presence of moral hazard is the price responsiveness of the individual-consumer medical services demand curve [Zeckhauser (1970), Phelps (2003), p. 328]. If the demand for a medical service is low price responsive, then cost sharing should be lower since the extent of moral hazard would be lower. If, on the other hand, the demand for a medical service is highly price responsive, then cost sharing should be higher since the extent of moral hazard would be higher. Thus, to the extent that the moral hazard effect varies by the type of medical condition associated with the visit, optimal cost sharing in health insurance should vary across services associated with different medical conditions.

[1] For a comprehensive list of these studies see Zweifel and Manning (2000). More recent studies are Finkelstein (2007), which analyzes the impact of Medicare on hospital utilization and spending, and Grabowski and Gruber (2007), which study the moral hazard effect in the demand for nursing home use.

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The theory of moral hazard also suggests that individual clinical characteristics should be taken into account in the design of optimal health insurance. Consumers may not be identical in terms of their marginal benefit schedules for health and therefore the marginal benefit schedule for a medical care service might vary across individuals based on health status [Pauly and Blavin (2008)]. As a consequence, the price responsiveness of the individual-consumer medical care demand may vary by health status, which suggests that the magnitude of the moral hazard effect might also differ across health status. Thus, to the extent that a particular medical service has different marginal benefit schedules across individuals based on health status, insurance design depends on that variation as well [Nyman (2003), Pauly and Blavin (2008)].

The value-based insurance design also emphasizes differential cost sharing [Fendrick and Chernew (2006), Chernew *et al*. (2007)]. The pioneers of this approach argue that cost sharing rules should be based on the value of medical services determined from the available clinical evidence and suggest that cost sharing should be lower for medical services with higher clinical benefits relative to costs. This approach to setting optimal cost sharing is also related to individual-consumer medical care demand elasticity. There are two cases to consider. First, suppose that consumers use demand curves identical to the marginal benefit curves generated by clinical evidence (i.e., perfect information). An individual who is more (less) likely to benefit from a medical service may be relatively unresponsive (responsive) to price. Thus, the variation in marginal clinical benefit configurations may be related to their respective variation in moral hazard effects, motivating differential cost sharing. Second, suppose that there is consumer misperception about the value of medical services (i.e., imperfect information), leading to smaller quantities of medical care demanded. Such imperfect information leads to lower cost sharing in order to bring medical services use to a particular marginal benefit level. However, keeping the extent of imperfect information constant, the more price elastic a particular medical service is, the higher its cost sharing should be due to higher moral hazard welfare losses [Pauly and Blavin (2008)]. As a consequence, even when individuals are imperfectly informed, the variation in price elasticity is as important as the extent of imperfect information, motivating differential cost sharing.

The existing insurance plans in the U.S. typically impose constant cost sharing regardless of the health status of the insured and the medical condition being treated. If the empirical results suggest variation in the magnitude of the moral hazard effect across health status *and* if this variation depends on the individual's medical condition, then optimal insurance for medical care should be designed to have differential cost sharing that varies across the health status

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of the insured *and* the medical condition being treated rather than the "one size fits all" cost sharing.[2] Such an insurance design with differential cost sharing would give the individual enough medical coverage but yields substantial reduction in moral hazard compared to a plan with uniform cost sharing [Zeckhauser (1970)].

The endogeneity of health insurance complicates the estimation of the relationship between insurance and medical care use. Unobserved health characteristics may influence the decision to enter a contract and thus create a self-selection bias (i.e., adverse selection). For example, the choice of insurance coverage may be affected by planned medical expenditures and expectations about medical care utilization. There is also self-selection into insurance arising from health plan behavior. Profit-maximizing insurance companies may attempt to control medical services use of relatively high-risk consumers or they may have incentives to distort the quality of services they offer to attract lower-risk consumers and discourage higher-risk individuals from purchasing insurance from them [Cutler and Zeckhauser (2000), Frank *et al*. (2000), Meer and Rosen (2004].[3] The adverse selection problem upwardly biases the moral hazard effect estimates, while self-selection arising from health plan behavior downwardly biases these estimates, if left uncontrolled. In estimating moral hazard effects, We recognize that private health insurance may not be exogenous. We also recognize the statistical challenges in analyzing count data. When combined with an endogenous treatment effect (i.e., the private insurance indicator), estimation of demand for medical services (which are recorded as count data) is less than straightforward, since traditional methods do not extend to models of discrete data when endogenous treatment effect is under consideration. For these reasons, we use the Generalized Method of Moments (GMM) estimation technique, which allows for analysis of discrete data in the presence of endogeneity.

We proceed as follows: Section 2 describes the data. Section 3 delineates the econometric methodology. Section 4 starts with discussing the specification test results dealing with instrument relevance, the endogeneity of private insurance and instrument validity. Next, this section presents the moral hazard effect estimates and robustness analyses assessing the stability of these

[2] There is some recent empirical works that emphasize the state specificity of optimal health insurance policies. For example, Chandra *et al*. (2010) argue that optimal health insurance for the elderly would be tied to underlying health status, with seriously ill patients facing lower cost sharing.

[3] For example, insurance companies could offer incentives to gatekeeper physicians not to refer patients to specialists.

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estimates. The section ends with a discussion about the health insurance design implications of the moral hazard effect estimates. Section 5 concludes.

1. THE DATA

The sample includes adults between the ages of 18 and 64, drawn from the Household Component of the 2002 Medical Expenditure Panel Survey (MEPS), its Office-Based Medical Provider Visits file and its Medical Conditions file. MEPS is co-sponsored 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. Observations containing veterans and individuals who are covered by Tricare insurance are removed from the data set since their medical services demand and access to medical services distinctly differ from the general population. Observations that are being designated as non-key and out-of-scope are also removed from the data set.[4] This leaves a sample of 17,419 observations. The definitions and the descriptive statistics of all regressors along with the dependent variables are reported in Table 1. Factors affecting ability to pay for medical care, health status, and condition-specific physician visits are categories of variables that require some explanation.

Table 1. Variable Definitions and Descriptive Statistics

This table presents descriptive statistics for the sample that includes adults between the ages of 18 and 64, drawn from the Household Component of the 2002 Medical Expenditure Panel Survey (MEPS), its Office-Based Medical Provider Visits file and its Medical Conditions file. The sample includes 17,419 observations.

Variable	Description of Variable	Mean	Std. Dev.
Demographics			
MALE	1 if male	0.42	0.49
AGE	Number of years old	39.55	12.59
AGE2	Age squared divided by 1,000	1.72	1.02
WHITE	1 if white	0.79	0.41
MARRIED	1 if married	0.56	0.50
COLLEGE	1 if at least high school graduate	0.41	0.49
NOREAST	1 if resides in the Northeast	0.16	0.37
MIDWEST	1 if resides in the Midwest	0.20	0.40

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

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SOUTH	1 if resides in the South	0.38	0.49
WEST	1 if resides in the West	0.26	0.44
URBAN	1 if the individual lives in an urban area	0.80	0.40
SICKPAY	1 if paid sick leave	0.38	0.48
EMPLOYED	1 if employed	0.70	0.46
INCOME	Family income divided by 1,000	47.28	46.90
Health Status			
ILLNESS	1 if poor or fair health	0.25	0.43
DISEASE	1 if at least one priority or long-term life threatening condition	0.46	0.50
DISABILITY	1 if at least one functional limitation	0.23	0.42
Instruments			
SELF-EMP	1 if self-employed	0.08	0.28
UNION	1 if the individual belongs to a labor union	0.08	0.26
FIRMSIZE	Size of workplace in terms of number of employees	97.48	164.37
Health Insurance			
PRIVATE	1 if privately insured	0.67	0.47
PUBLIC	1 if publicly insured	0.13	0.34
Condition-Specific Physician Services Use			
DOCCHRON	Chronic condition related physician office visits	1.41	3.49
DOCACUTE	Acute condition related physician office visits	1.49	4.37

2. ABILITY TO PAY FOR MEDICAL SERVICES

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

Opportunity cost of time may also affect access to medical care. To represent this factor, we create a variable that indicates whether the individual’s employer paid sick leave. If an individual has paid sick leave, he is expected to use more medical services due to decreased time price of medical care, since sick leave insures the time costs of medical care.

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3. HEALTH STATUS

We use self-reported health index and medical conditions - identified by disease and disability - to capture health status during the year. For each of these three health status variables, we construct a criterion for a binary indicator. Self-reported health index, which may reflect illness, is based on the answer to the following question, asked *three* times during the year: "In general, would you say your health is excellent, very good, good, fair or poor?" The answer to this question is coded on a 1-5 scale, with 1 being excellent, 2 as very good, 3 as good, 4 as fair, and 5 as poor. We then create a variable (ILLNESS) that indicates whether the individual is in poor or fair health *at any time* during the year.[5] Disease is identified by the existence of priority or long-term life threatening health conditions during the year (DISEASE).[6] We recognize the presence of disability based on functional limitation status and use a variable that indicates whether the individual has a functional limitation *at any time* during the year (DISABILITY).[7]

4. CONSTRUCTION OF CONDITION SPECIFIC PHYSICIAN OFFICE VISITS

Physician visits are constructed using the number of office based visits to a medical physician *over the last year*, 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. Physician visits are classified as chronic or acute care using a coding scheme developed by Hwang *et al*. (2001), which categorizes each three-digit ICD-9-CM

[5] This cut-off in the self-reported health index is very common in the health economics literature. See, for example, Wedig (1988), Meer *et al*. (2003) and Buckley *et al*. (2004).

[6] Disease indicates whether the person has one of the following priority conditions during the year: long-term life threatening conditions such as cancer, diabetes, emphysema, high cholesterol, 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.

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

1. Needs help with instrumental activities of daily living such as doing laundry or taking medications.
2. Needs help with activities of daily living such as bathing or dressing.
3. Difficulty in performing certain physical activities such as walking, lifting or climbing stairs.
4. Limitations in work, housework or school.
5. Cognitive limitations such as confusion or memory loss.
6. Sensory limitations such as visual or hearing impairments.

condition code as a chronic or an acute condition.[8] Hwang *et al*. (2001) defined a chronic condition as a condition which lasts or is expected to last 12 months or longer, and results in functional limitations and/or the need for ongoing medical intervention. Based on this description a physician panel of 5 internists determined whether each three-digit ICD-9-CM condition code represented a chronic or an acute condition. If the individual went to the doctor for treatment of a specific condition[9] and if this condition is in Hwang *et al*.'s (2001) list of chronic conditions, then we classify the visit as chronic care (DOCCHRON). If, on the other hand, the consultation with the doctor is in reference to a specific condition and if this condition is in Hwang *et al*.'s (2001) list of acute conditions, then we classify the visit as acute care (DOCACUTE).

5. EMPIRICAL MODEL

The first step in estimating moral hazard effects is to estimate the demand for each physician visit category. Let $f(y\,|X, PRIVATE, PRIVATE * H, \lambda)$ be the conditional probability density function of physician services use. $y = 0, 1, 2, \ldots$ is the count dependent variable that represents the number of physician visits over a stated period of time; X is a vector of explanatory variables including demographics, a variable that indicates whether the individual is publicly insured, and health status indicators; PRIVATE indicates whether the individual is privately insured; H is a health status indicator; and λ is the interpersonal heterogeneity component. For each physician visit category, three different regression specifications are estimated, depending on which binary health status indicator is interacted with the private health insurance indicator. As a consequence, the definitions of "healthy" and "sickly" groups differ across the specifications. For example, if the health groups are based on the DISABILITY variable, then an individual belongs to the sickly group if the DISABILITY variable takes on the value 1. Otherwise, the individual belongs to the healthy group.

Since we analyze count data for the demand for physician visits, it is natural to employ a Poisson or a Negative Binomial regression model. Either regression

[8] ICD-9-CM refers to "International Classification of Diseases, Ninth Revision, Clinical Modification." Prof. Wenke Hwang graciously provided the list of chronic and acute conditions based on the reference to three-digit ICD-9-CM condition codes. A complete list of these conditions with their respective three-digit ICD-9-CM codes is available upon request.

[9] The medical conditions reported by the Household Component data respondents were recorded by the interviewer as verbatim text. These responses were then coded to fully-specified ICD-9-CM codes by professional coders. Due to confidentiality restrictions, MEPS does not make provider-reported condition information publicly available.

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model assumes that the unobserved heterogeneity and the regressors are statistically independent. PRIVATE, however, is likely endogenous to the use of physician services. To deal with this issue, we follow Mullahy (1997), who provide conditional moment restrictions to estimate count data models with endogenous regressors using the Generalized Method of Moments (GMM) method. Note that if the conditional probability density function of y is Poisson or Negative Binomial, then its conditional mean is

$$E[y \mid X, PRIVATE, PRIVATE * H, \lambda] = \exp(X\beta + PRIVATE\delta_1 + PRIVATE * H\delta_2 + \lambda) \quad (1)$$

This expression for the conditional mean motivates the exponential regression function

$$y = \exp(X\beta + PRIVATE\delta_1 + PRIVATE * H\delta_2)v + \tau \quad (2)$$

$v = \exp(\lambda)$, the interpersonal heterogeneity component, is unobservable and varies over the population.[10] Since a constant term is included in X, $E[v] = 1$ can be assumed without loss of generality. It is also assumed that $E[\tau \mid X, PRIVATE, PRIVATE * H, \lambda] = 0$, i.e., τ is a regression specification error. Finally, to incorporate the possibility that some regressors are endogenous, it is assumed that $E[v \mid X, PRIVATE, PRIVATE * H] \neq 1$. This is an exponential regression model for nonnegative dependent variables with multiplicative unobserved heterogeneity with the additional assumption that some regressors are endogenous.

Since endogeneity implies that

$$E[v \mid X, PRIVATE, PRIVATE * H] \neq E[v] = 1 \quad (3)$$

suppose that Z is a vector of instrumental variables with

$E[\tau \mid X, PRIVATE, PRIVATE * H, Z] = 0$ and $E[v \mid Z] = 1$. Mullahy (1997) shows that a consistent GMM estimation can then be based on the conditional moment restriction

$$E[(v-1) \mid Z] = E[\exp(-X\beta - PRIVATE\delta_1 - PRIVATE * H\delta_2)y - 1 \mid Z] = 0. \quad (4)$$

Mullahy's (1997) estimator is a semiparametric nonlinear instrumental variables (IV) estimator and uses the transformed residual

[10] This model is motivated by treating the observables $(X, PRIVATE, PRIVATE * H)$ and the unobservable λ symmetrically. As Mullahy (1997) notes, it is generally assumed in the existing count data literature that the observables and the unobserved heterogeneity term play symmetric roles in the data-generating process.

$(\nu - 1) + \exp(-X\beta - PRIVATE\,\delta_1 - PRIVATE * H\delta_2)\tau$ as the residual function.[11]

The efficient GMM estimator, given the instruments, is found by an iterative minimization procedure. In the first step the model is estimated by GMM using a weighting matrix $\widehat{W}$ (i.e., inverse of the covariance matrix of the moment conditions) which imposes the assumption of conditional homoskedasticity on the matrix of squared transformed residuals $\widehat{\Omega}$ (i.e., setting $\widehat{W} = [Z'Z]^{-1}$). This is essentially a nonlinear IV estimation using the moment restriction in (4) and yields consistent but inefficient estimators. Using the first-step coefficient estimates, the matrix of squared transformed residuals is estimated assuming heteroskedasticity of unknown form. This estimated matrix is then used to form the optimal weighting matrix $\widehat{W} = \left[Z'\widehat{\Omega}Z\right]^{-1} = \left[\sum_{i=1}^{N}(\hat{\nu} - 1)^2\, Z'Z\right]^{-1}$. Thus, a heteroskedasticity-consistent estimator of the covariance matrix of the moment conditions is estimated using the “sandwich” approach to robust covariance estimation. In the second step, the model is estimated by GMM using the estimated optimal weighting matrix $\widehat{W}$ and the moment restriction in (4). This procedure is iterated by obtaining the transformed residuals from the two-step GMM estimator, using these residuals to estimate a new optimal weighting matrix, and using this new optimal weighting matrix to calculate the three-step GMM estimator, and so forth until the squared difference between the two consecutive estimated coefficient vectors is less than 10^{-6} with a maximum iteration of 20. The estimated variance-covariance matrix of this iterative GMM estimator is robust to the presence of heteroscedasticity.

6. IDENTIFICATION

The dummy endogenous variable $PRIVATE$ is characterized by a latent variable whose determinants are a vector of variables including demographics and health status indicators, and a vector (Z_1) of exogenous variables that are *independent of physician services use*. To implement the GMM estimation we first estimate a probit model for the presence of private health insurance and obtain predicted probabilities $\widehat{\Phi}$, (Φ is the standard normal cumulative distribution function). We then perform the GMM estimation based on the conditional moment restriction in (4) using instruments $Z = (X, \widehat{\Phi}, \widehat{\Phi}H$

[11] Using the standard residual function as a conditional moment restriction in the GMM estimation of an exponential conditional mean with multiplicative unobserved heterogeneity does not yield consistent parameter estimates. The main problem is that ν is not additively separable from the observables in the standard residual function. To deal with this problem, Mullahy (1997) transforms the regression model to obtain a residual function in which ν is additively separable from the potential endogenous regressors.

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and Z_1). Thus, using the predicted probabilities $\widehat{\Phi}$ from the probit regression, instruments $\widehat{\Phi}$ and $\widehat{\Phi}H$ are constructed for PRIVATE and PRIVATE*H, respectively.[12] The effect of private health insurance on physician services use is identified by using variables that are independent of physician services use (i.e., Z_1). We use employment characteristics such as the size of the company where the individual works (FIRMSIZE), whether the individual is self-employed (SELF-EMP), and whether the individual belongs to a union (UNION) as identifying instruments.

Firm size is a strong predictor of private health insurance coverage. Greater risk pooling and economies of scale in the purchase and administration lowers the price per worker for purchasing fringes. Thus, large firms are more likely to offer health insurance benefits to their employees. Self-employment status is another good predictor of private health insurance coverage. For comparable health benefits, health insurance costs are 10-40% higher for the self-employed [Holtz-Eakin *et al*. (1996)] for reasons of adverse selection or administrative costs. Thus, since the self-employed face a higher price for health insurance, they are less likely to be insured than those who are not self-employed [Holtz-Eakin *et al*. (1996), Hamilton (2000)]. Union membership is also a good predictor of private health insurance coverage, leading to higher probability of obtaining insurance [Pauly and Herring (2007)]. Freeman (1981) argues that the likelihood that an employer provides fringe benefits is greater if the supply price of fringes – wages workers would forgo to obtain the benefit – facing an employer is higher. Unionism raises the supply price of health insurance benefits because the union firm gives greater weight to the preferences of inframarginal workers (i.e., relatively older and permanent employees) relative to the nonunion firm [Freeman (1981), Olson (2002)] and these workers have greater desires for health insurance benefits. Consequently, union members are more likely to be insured than nonmembers.

It is also important to note that many recent studies have used these variables as identifying instruments in models of medical care use. See Johnson and Crystal (2000), Olson (2002), Bhattacharya *et al*. (2003), Pauly (2005), Deb and Trivedi (2006), and Deb *et al*. (2006) for firm size; Meer and Rosen (2004), and Deb and Trivedi (2006) for self-employment status; and Johnson and Crystal (2000), Olson (2002), and Deb and Trivedi (2006) for union membership. *Nevertheless, specification tests dealing with the relevance and the validity of these instruments, and a series of robustness analyses to further evaluate the validity of these instruments will be provided later in the paper.*

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[12] As Wooldridge (2002, p. 626) suggests, if $\widehat{\Phi}$ is an instrument for $PRIVATE$, then the natural instrument for $PRIVATE * H$ is $\widehat{\Phi}H$.

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7. MORAL HAZARD EFFECTS

We define the moral hazard effect with the average treatment effect of insurance. For an individual who does *not* belong to the health group defined by H (i.e., "Healthy"), the moral hazard effect is $MHE(H=0)=\frac{E[y\mid X,\ PRIVATE=1,\ H=0]}{E[y\mid X,\ PRIVATE=0,\ H=0]}=\exp(\delta_1)\simeq 1+\delta_1$, for δ_1 small. Thus, the coefficient of $PRIVATE$ is approximately the proportional average treatment effect of insurance for a randomly chosen individual from the health group defined by $H=0$. In other words, the coefficient of $PRIVATE$ can be interpreted as the percentage change in physician care utilization for the healthy due to the presence of private health insurance. Similarly, for an individual who belongs to the health group defined by $H=1$ (i.e., "Sickly"), the moral hazard effect is $MHE(H=1)=\frac{E[y\mid X,\ PRIVATE=1,\ H=1]}{E[y\mid X,\ PRIVATE=0,\ H=1]}=\exp(\delta_1+\delta_2)\simeq 1+\delta_1+\delta_2$, for $(\delta_1+\delta_2)$ small. Thus, the coefficient of the interaction term $PRIVATE*H$ is approximately the difference in moral hazard effects expressed in percentage points between the two health groups.

8. RESULTS

8.1. Specification Tests

Three types of specification tests are performed: tests dealing with instrument relevance, the endogeneity of private insurance and instrument validity.

The relevance of identifying instruments requires that FIRMSIZE, SELF-EMP and UNION must be correlated with private insurance after conditioning on other variables affecting private insurance. If the instruments are weakly correlated with the endogenous explanatory variable, then IV/GMM estimates are biased in the same direction as the endogeneity-uncorrected estimates. The magnitude of this bias depends on the *R*-squared between the excluded instruments and the endogenous variable in a *linear* model: as this multiple correlation increases, the bias of the IV estimator decreases. The finite sample bias of the linear IV estimator can also be expressed in terms of the *F*-statistic on the excluded instruments [Bound *et al*. (1995)]. Indeed, Stock *et al*. (2002) suggest that the first-stage *F*-statistic on the excluded instruments can be used to ascertain whether these instruments are weak. It is therefore common practice to report the test statistic on the joint significance of the excluded instruments in the first stage of *nonlinear* IV models [e.g., Deb and Trivedi (2006)].

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The results of the probit regression appear in Table 2. The overall predictive power of the probit regression is considerably high. The pseudo *R*-squared statistic is 0.347 and the percentage of observations correctly predicted is 81.5.[13] The majority of the explanatory variables are highly significant and their parameter estimates are consistent with those obtained in previous studies.[14] The probit regression results also reveal that the identifying variables are highly significant and have the predicted signs. As the size of workplace increases, individuals are more likely to be covered by private insurance. Union members are more likely to have private insurance. Being a union member increases the predicted probability of having private insurance by 11 percentage points. Being self-employed decreases the predicted probability of obtaining private insurance by 5 percentage points. As mentioned above, the joint significance test on these identifying variables is useful as a guide to the quality of GMM estimates. The Wald test statistic with three degrees of freedom is 228.98, which reveals that the identifying instruments are strongly jointly significant in the first stage.

Table 2. Probit Regression for Private Health Insurance

This table presents the coefficient estimates, *t*-statistics and marginal effects estimated using the Probit model for the presence of private health insurance. The results of this regression are especially used for assessing the relevance of the identifying instruments FIRMSIZE, SELF-EMP and UNION. The pseudo *R*-squared is 0.347 and the percent of observations correctly predicted is 81.5. *** indicates statistical significance at .01 or better. ** indicates statistical significance at .05. * indicates statistical significance at .10. N.A. stands for Not Applicable.

Variable	Coefficient	*t*-stat	Marginal Effects
CONSTANT	0.25**	2.05	N.A.
MIDWEST	0.18***	4.22	0.05

[13] 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.

[14] Individuals who are female, white, married, employed, with higher incomes, and who have a higher educational attainment have a higher probability of having private insurance. Under the hypothesis of adverse selection, individuals who anticipate poor health for them are more likely to purchase private insurance because of the corresponding increase in the expectation of medical services use. Although disease increases the probability of having private insurance, disability and illness decrease this probability, which casts doubt on the existence of adverse selection for observable variables. This finding is consistent with those of previous studies such as Vera-Hernandez (1999) and Jones *et al*. (2004).

SOUTH	-0.12***	-3.10	-0.03
WEST	-0.19***	-4.87	-0.06
URBAN	-0.08***	-2.65	-0.02
AGE	-0.06***	-9.01	-0.02
AGE2	0.73***	9.46	0.21
MALE	-0.05*	-1.84	-0.01
WHITE	0.06*	1.93	0.02
MARRIED	0.25***	8.90	0.07
COLLEGE	0.47***	17.22	0.13
INCOME	0.02***	31.43	0.004
EMPLOYED	0.18***	5.56	0.05
SICKPAY	0.89***	25.34	0.23
ILLNESS	-0.31***	-9.93	-0.09
DISABILITY	-0.12***	-3.71	-0.04
DISEASE	0.19***	6.73	0.05
FIRMSIZE	0.001***	10.96	0.0003
SELF-EMP	-0.15***	-3.34	-0.05
UNION	0.47***	6.62	0.11

We also employ a linear probability model of the first stage (with robust standard errors) in order to report partial *R*-squared and *F*-statistic on the excluded instruments. The partial *R*-squared of excluded instruments is 0.0073, whereas the *F*-statistic with three degrees of freedom is 65.79. According to Stock *et al*. (2002), if the number of excluded instruments is 3, the 5% critical value to reject the null hypothesis that instruments are weak is 9.08. Thus, the instruments have useful prediction and hence are relevant.

Finally, in nonlinear GMM models, if GMM estimators are sensitive to changes in the sample, then there may be weak instruments problem [Stock *et al*. (2002)]. The estimated moral hazard effects are not sensitive to variations in sample coverage, such as excluding the self-employed, unemployed and publicly insured [Tables 6-7]. Taken together, the evidence suggests that it is very unlikely that the instruments pose a weak identification problem.

We test for endogeneity of private health insurance by estimating two model formulations and applying the Hausman test. The first formulation (NB) treats the binary private insurance variable as exogenous and is the standard Negative Binomial regression model; the second is the GMM model described above. The formal hypothesis to be tested is that private insurance is *exogenous*.[15] If this hypothesis is rejected, then the appropriate specification is the GMM formulation. The results of the Hausman tests appear in Table 3. We find evidence to reject exogeneity of insurance in the demand for all physician services. Furthermore, this endogeneity matters. Comparison of the correctly specified GMM model formulation results with those emanating from the NB

[15] Note that testing whether private insurance is exogenous requires testing whether PRIVATE and PRIVATE*H are both uncorrelated with the unobserved heterogeneity term in the physician services demand regressions.

model shows that the estimates of moral hazard are sharply understated if the endogeneity is ignored (Table 4). This result suggests that self-selection arising from health plan behavior more than offsets the adverse selection effect.[16]

Table 3 . Specification Tests

This table presents specification test results, with *p*-values in parenthesis, dealing with instrument validity (i.e., testing for over identifying restrictions) and endogeneity of private health insurance. Over identification tests are based on Hansen's *J*-statistic with three degrees of freedom. A rejection of this test casts doubt on the validity of identifying restrictions. The hypothesis that private insurance is exogenous is tested by comparing the Negative Binomial regression model, which treats the private insurance variable as exogenous, and the GMM model using the Hausman test based on the coefficients of PRIVATE and PRIVATE*H.

	H=ILLNESS		***H=DISABILITY***		***H=DISEASE***	
	DOCCHRON	**DOCACUTE**	**DOCCHRON**	**DOCACUTE**	**DOCCHRON**	**DOCACUTE**
Hausman Test	12.43	21.70	13.80	21.75	7.38	19.45
	(0.002)	(< 0.0001)	(0.001)	(< 0.0001)	(0.02)	(< 0.0001)
Correct Specification	GMM	GMM	GMM	GMM	GMM	GMM
***J*-Statistic**	5.35	2.74	5.03	2.62	4.48	3.05
	(0.15)	(0.43)	(0.17)	(0.45)	(0.21)	(0.38)

In order for the identifying instruments to identify the effect of private health insurance on physician services use, it must be the case that these variables are validly excluded from the physician services use regressions. Hansen's *J*-statistic is used to test for these over identifying restrictions. A rejection of this test casts doubt on the validity of identifying variables. The results of Hansen's over identification tests appear in Table 3. For each physician service, the value of the *J*-statistic is tolerably small. Thus, overall, the hypothesis of correct specification is not rejected, which suggests that the models are reasonably well specified and the over identifying restrictions have not been violated. *Nevertheless, a series of robustness analyses will be provided later in the paper (Section 4.3) to further evaluate the validity of the identifying instruments.*

8.2. Moral Hazard Effects

Moral hazard effect results appear in Table 4.[17] The results suggest that the moral hazard effect is significantly *higher* for the healthy for chronic condition

[16] This result is consistent with the findings of Meer and Rosen (2004), Jones *et al*. (2004) and Deb *et al*. (2006) who also find that self-selection arising from health plan behavior more than offsets the adverse selection effect.

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related physician visits (DOCCHRON), irrespective of the regression specification regarding the interaction between the private health insurance and health status indicators. The results on the other hand indicate that there is no appreciable difference in moral hazard effects between the healthy and sickly groups for acute condition related physician visits (DOCACUTE) for the two regression specifications where PRIVATE is interacted with ILLNESS and DISABILITY, respectively, while the moral hazard effect for DOCACUTE is significantly higher for the healthy for the regression specification where PRIVATE is interacted with DISEASE.

Table 4. Moral Hazard Effects

This table presents the moral hazard effect estimates and *t*-statistics (in parenthesis). The first and second columns report the coefficient of private health insurance (PRIVATE) and the coefficient of private health insurance interacted with a health status indicator (PRIVATE*H), respectively, estimated by the GMM regressions reported in the Appendix. The third column is the sum of the coefficients of PRIVATE and PRIVATE*H, and its precision takes into account the standard errors of PRIVATE and PRIVATE*H. The last two columns report the coefficients of PRIVATE and PRIVATE*H, respectively, estimated by the unreported Negative Binomial regressions. *** indicates statistical significance at .01 or better. ** indicates statistical significance at .05. * indicates statistical significance at .10.

	GMM Specification			*NB Specification*	
	Healthy	**Sickly-Healthy**	**Sickly**	**Healthy**	**Sickly-Healthy**
H=ILLNESS					
DOCCHRON	1.48***	-0.47**	1.01***	0.70***	-0.09
	(5.28)	(-2.54)	(3.10)	(11.86)	(-1.23)
DOCACUTE	1.62***	0.15	1.77***	0.67***	0.06
	(7.76)	(0.78)	(6.02)	(13.91)	(0.87)
H=DISABILITY					
DOCCHRON	1.45***	-0.66***	0.79**	0.73***	-0.20***
	(5.24)	(-3.52)	(2.46)	(12.82)	(-2.60)
DOCACUTE	1.69***	-0.002	1.69***	0.71***	-0.07
	(7.75)	(-0.01)	(5.34)	(15.12)	(-0.98)
H=DISEASE					
DOCCHRON	1.42***	-0.41**	1.01***	0.74***	-0.12
	(4.98)	(-2.42)	(3.69)	(10.82)	(-1.62)
DOCACUTE	1.77***	-0.27*	1.50***	0.81***	-0.25***
	(7.86)	(-1.90)	(6.08)	(15.32)	(-3.92)

These findings have some intuitive appeal. Expenditures on chronic condition related physician services are foreseen and continuing expenses since treatment

[17] The full regression results for the demand for physician visits appear in the Appendix, where for each physician visit category we report the estimation results for the model specification indicated by the Hausman test.

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for most of such diseases is designed to reduce the severity of consequences rather than to cure. A relatively healthy individual may seek physician care for a routine maintenance visit or for the treatment of a less serious chronic condition. Although healthy individuals with insurance are expected to seek care for such reasons, those without insurance are expected to seek minimal such care. A relatively sickly individual on the other hand may seek physician care due to a recent flare-up of a chronic condition or due to a serious chronic condition. This suggests that the relatively sickly are likely to seek such care, although the insured would, of course, consume more. This in turn suggests that chronic condition related physician care for the sickly is less price responsive than the same type of care for the healthy, which may explain why the moral hazard effect is higher for the healthy for chronic condition related physician visits. An acute condition, on the other hand, is an unforeseen illness of short duration and the individual has less ability to defer treatment of such diseases. This suggests that the decision to seek physician care in response to an acute condition may not depend on the individual's overall health status, which may explain why, taken together, the results do not support a significant difference in moral hazard effects across health groups for acute condition related physician visits.
In addition to discussing whether there is a significant difference in moral hazard effects between the healthy and sickly, it would be informative to discuss whether either health status groups actually exhibits moral hazard and to assess the economic significance of these effect estimates. The moral hazard effect estimates for the healthy are provided in Table 4 in the columns headed "healthy. "The healthy have significant moral hazard for each physician service category. The moral hazard effect for the sickly is the sum of the effect estimates in the columns headed "healthy" and "sickly – healthy," and the estimates are provided in the column headed "sickly." The sickly also exhibits significant moral hazard for each physician service. The moral hazard effect for the healthy for DOCCHRON is roughly 145%, whereas for the sickly it ranges between 79-101%, depending on the regression specification. These estimates suggest that the insured healthy consumes 145% more chronic condition related physician office visits relative to those healthy individuals without insurance, whereas the insured sickly consumes 79-101% more chronic condition related physician office visits relative to the sickly without insurance. The moral hazard effect for DOCACUTE for the healthy ranges between 162-177%, whereas for the sickly it ranges between 150-177%.

Although differences in data and econometric techniques preclude exact comparisons, our moral hazard effect estimates for physician services seem large relative to the findings of previous studies. According to the pathbreaking RAND health insurance experiment [Manning *et al*. (1987)], expected

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physician visits for individuals randomly assigned to a *fee-for-service* plan with 95% coinsurance is 2.73, whereas expected visits for those facing a fee-for-service insurance plan with 0% coinsurance is 4.55. In other words, the moral hazard effect of going from the 95% coinsurance plan to the free plan is 67%. The RAND health insurance experiment, however, was not designed to analyze the difference in medical care utilization between individuals with and without health insurance. It was designed to address the impact of varying coinsurance rates on utilization by the *insured* [Lohr *et al*. (1986)]. Moreover, individuals assigned to an insurance plan with 95% coinsurance rate faced an actual average coinsurance rate of 31% due to stop-loss provisions [Spillman (1992)]. Thus, comparing the moral hazard effect of going from the 95% coinsurance plan to the free plan from the RAND study with our moral hazard effect estimates may not be appropriate.

There are some studies that analyze the moral hazard effect of private health insurance by comparing medical care consumption of those with and without private insurance [Spillman (1992), Hahn (1994), Marquis and Long (1994)]. These studies find that the moral hazard effect for physician visits ranges between 69% and 100%. None of these papers, however, deal with the endogeneity of private insurance. The discrepancy between our estimates and those of the prior literature is most probably due to the fact that we employ an estimation strategy which explicitly controls for the endogeneity of private insurance. This is evident if one analyzes our moral hazard effect estimates from the Negative Binomial regressions where the endogeneity of private health insurance is not taken into account. These effect estimates are of a comparable magnitude of the gap in physician service utilization between individuals with and without private insurance found in earlier studies.

9. ROBUSTNESS CHECKS REGARDING THE VALIDITY OF INSTRUMENTS

In this section we discuss two types of robustness checks in order to assess the stability of our results to the validity of identifying instruments.[18] The first robustness check constructs three sets of GMM estimates of moral hazard effects using (UNION, FIRMSIZE), (SELF-EMP, FIRMSIZE) and (SELF-

[18] For example, the validity of self employment status as an instrument may be questioned. There might be unobservable variables that affect both medical services use and the propensity to become self-employed; it may be that self-employment requires a lot of energy and thus individuals who are too healthy tend to enter self-employment [Perry and Rosen (2001)]. However, it has been shown that this concern is not much of a problem. Using MEPS, Meer and Rosen (2004) demonstrate that self-employment status is a valid instrument in a model of medical care use and health insurance demand.

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EMP, UNION) as identifying instruments one at a time. In other words, we re-estimate all regressions using the smaller set of instruments, excluding each instrument from the full set one at a time. The intuition behind this robustness analysis is as follows: the basis of the standard over identification test is that if two instruments are valid, then they both yield consistent estimates of the moral hazard effect and thus the difference between the estimators should be small. If not, then at least one of the instruments is not valid. As a consequence, if the moral hazard effects using different instruments provide the same interpretation of the data, then the credibility of instruments is enhanced. We also test the validity of each excluded instrument using the *C*-statistic, which tests the exogeneity of a subset of instruments whose validity is in suspect. *C*-statistic is defined as the difference of the *J*-statistic of the regression with the full set of instruments and the regression with the smaller set of instruments. Under the null hypothesis that both the smaller set of instruments and the suspect instrument are valid, the *C*-statistic is distributed as chi-squared in the number of instruments tested.[19] Failure to reject the null hypothesis requires that the *C*-statistic and the *J*-statistics for the regressions with both the full set of instruments and the smaller set of instruments should all be small.

The moral hazard effect estimates for the regression specifications with the smaller set of instruments and their respective *J*- and *C*-statistics appear in Table 5. The effect estimates are almost the same as those reported in Table 4. The values of the *J*-statistic are remarkably small. The *C*-statistic is also tolerably small for all instruments and physician visits, except maybe for FIRMSIZE in the demand for chronic condition related physician visits (DOCCHRON, see Table 5, Panel C).

The second robustness check discusses the sensitivity of estimated moral hazard effects to variations in sample coverage. Since the insurance decision of the self-employed and unemployed could especially represent endogeneity, to assess the robustness of our results to this issue, following the lead of Meer and Rosen (2004) and Deb and Trivedi (2006), we re-estimate our models for a subsample excluding the group of self-employed and for another subsample excluding the unemployed.[20]

[19] Note that the specification with the smaller set of instruments is presumed to be consistent under the null and the alternative.

[20] The group of unemployed includes those individuals who are involuntarily out of work. Among the group of *not-employed*, students, retired workers, those who have never been employed, those who are unable to work because they are disabled, and those who are taking care of home and family are kept in the sample since they are not involuntarily out of work.

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Table 5. Subset of Instruments Analysis

This table presents specification tests dealing with the validity of identifying instruments. Three sets of GMM estimates of moral hazard effects are constructed excluding each instrument one at a time and using the remaining two as identifying instruments. The first column in each panel reports the moral hazard effects and *t*-statistics (in parenthesis) for the healthy group. The second column reports the difference in moral hazard effects between the two health groups. The third column reports the over identification test results with two degrees of freedom (*p*-values in parenthesis). The final column reports the *C*-statistic, which is defined as the difference of the *J*-statistic of the regression with the full set of instruments and the regression with the smaller set of instruments. Under the null hypothesis that both the smaller set of instruments and the suspect instrument are valid, the *C*-statistic is distributed as chi-squared in the number of instruments tested. *** indicates statistical significance at .01 or better. ** indicates statistical significance at .05. * indicates statistical significance at .10.

A. Moral Hazard Effects: UNION and FIRMSIZE are Identifying Instruments

	Healthy	Sickly-Healthy	*J*-Statistic	*C*-Statistic
H=ILLNESS				
DOCCHRON	1.56***	-0.48**	4.41	0.94
	(5.04)	(-2.55)	(0.11)	(0.33)
DOCACUTE	1.62***	0.14	2.61	0.13
	(7.72)	(0.73)	(0.27)	(0.72)
H=DISABILITY				
DOCCHRON	1.53***	-0.64***	4.15	0.88
	(5.06)	(-3.39)	(0.13)	(0.35)
DOCACUTE	1.69***	-0.01	2.46	0.16
	(7.69)	(-0.07)	(0.29)	(0.69)
H=DISEASE				
DOCCHRON	1.48***	-0.40**	3.90	0.58
	(4.85)	(-2.35)	(0.14)	(0.45)
DOCACUTE	1.78***	-0.27*	2.95	0.10
	(7.81)	(-1.90)	(0.23)	(0.75)

Moral Hazard Effects: SELF-EMP and FIRMSIZE are Identifying Instruments

	Healthy	Sickly-Healthy	*J*-Statistic	*C*-Statistic
H=ILLNESS				
DOCCHRON	1.54***	-0.48***	5.21	0.14
	(5.35)	(-2.60)	(0.07)	(0.71)
DOCACUTE	1.67***	0.19	1.37	1.37
	(7.49)	(0.93)	(0.50)	(0.24)
H=DISABILITY				
DOCCHRON	1.51***	-0.65***	4.78	0.25
	(5.36)	(-3.49)	(0.09)	(0.62)
DOCACUTE	1.73***	0.05	1.30	1.32
	(7.46)	(0.25)	(0.52)	(0.25)
H=DISEASE				
DOCCHRON	1.48***	-0.41**	4.09	0.39

	(5.11)	(-2.44)	(0.13)	(0.53)
DOCACUTE	1.82***	-0.24*	1.39	1.66
	(7.60)	(-1.70)	(0.50)	(0.20)

B. Moral Hazard Effects: SELF-EMP and UNION are Identifying Instruments

	Healthy	Sickly-Healthy	*J*-Statistic	*C*-Statistic
H=ILLNESS				
DOCCHRON	1.61***	-0.49**	1.70	3.65
	(5.25)	(-2.53)	(0.43)	(0.06)
DOCACUTE	1.68***	0.12	2.14	0.60
	(7.19)	(0.63)	(0.34)	(0.44)
H=DISABILITY				
DOCCHRON	1.60***	-0.72***	1.64	3.39
	(5.18)	(-3.81)	(0.44)	(0.07)
DOCACUTE	1.74***	-0.01	2.09	0.53
	(7.15)	(-0.07)	(0.35)	(0.47)
H=DISEASE				
DOCCHRON	1.56***	-0.48***	1.16	3.32
	(4.98)	(-2.80)	(0.56)	(0.07)
DOCACUTE	1.83***	-0.29*	2.50	0.55
	(7.27)	(-1.99)	(0.29)	(0.46)

The results are depicted in Table 6. Once again the estimated moral hazard effects retain the same sign and are remarkably similar to those estimated using the full original sample.

Table 6. Moral Hazard Effects: Variations in Sample Coverage

This table presents the results of the sensitivity of estimated moral hazard effects to variations in sample coverage. All regressions are re-estimated by the GMM method for a subsample excluding the group of self-employed and for another subsample excluding the unemployed. For each sample, the first column reports the moral hazard effect and *t*-statistics (in parenthesis) for the healthy group. The second column reports the difference in moral hazard effects between the two health groups. The final column for each sample reports the over identification tests with three degrees of freedom for the sample without the unemployed and with two degrees of freedom for the sample without the self-employed (*p*-values in parenthesis). *** indicates statistical significance at .01 or better. ** indicates statistical significance at .05. * indicates statistical significance at .10.

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	Sample without the Self-Employed			*Sample without the Unemployed*		
	Healthy	**Sickly-Healthy**	***J*-Statistic**	**Healthy**	**Sickly-Healthy**	***J*-Statistic**
H=ILLNESS						
DOCCHRON	1.50***	-0.44**	2.99	1.55***	-0.59***	5.53
	(5.40)	(-2.44)	(0.22)	(5.45)	(-3.07)	(0.14)
DOCACUTE	1.73***	0.20	1.36	1.58***	0.20	2.83
	(7.83)	(0.94)	(0.51)	(7.18)	(1.00)	(0.42)
H=DISABILITY						
DOCCHRON	1.50***	-0.67***	2.89	1.51***	-0.75***	5.08
	(5.54)	(-3.55)	(0.24)	(5.42)	(-3.96)	(0.17)
DOCACUTE	1.80***	0.07	1.26	1.67***	0.02	2.67
	(7.70)	(0.33)	(0.53)	(7.24)	(0.11)	(0.45)
H=DISEASE						
DOCCHRON	1.42***	-0.35**	2.80	1.48***	-0.52***	4.44
	(5.16)	(-2.11)	(0.25)	(5.09)	(-3.01)	(0.22)
DOCACUTE	1.91***	-0.26*	1.54	1.76***	-0.25*	3.03
	(7.71)	(-1.79)	(0.46)	(7.36)	(-1.68)	(0.38)

10. ENDOGENEITY OF PUBLIC INSURANCE

A dummy variable that indicates whether the individual has public insurance (PUBLIC) is included as a regressor in the demand for physician visits regressions and is assumed to be exogenous to the demand for physician visits. While one may reasonably claim that Medicare insurance is exogenous (because only the elderly and disabled are eligible), it is possible that Medicaid coverage is not. The reason is that since basic Medicaid eligibility is via poverty thresholds, there may be unhealthy individuals without (adequate) health insurance "spending down" their resources in order to qualify for Medicaid.

Established instruments that affect the probability of obtaining public insurance but are unrelated to health status are state-policy variables that influence the ease with which individuals can obtain public insurance, such as state income eligibility threshold and state income threshold for the medically-needy program [Bhattacharya *et al*. (2003)]. Unfortunately, MEPS does not provide the state in which the individual resides and hence these variables cannot be constructed. Therefore, to explore the sensitivity of our results to the possible endogeneity of public insurance, individuals who have public insurance are eliminated from the sample and the econometric models are re-estimated. The results of this robustness analysis are reported in Table 7. Overall, the patterns in the estimated moral hazard effects are the same as those reported in Table 4.

Table 7. Moral Hazard Effects: Sample without the Publicly Insured

This table presents the results of the sensitivity of estimated moral hazard effects to the endogeneity of public insurance. All regressions are re-estimated by the GMM method for a subsample excluding the publicly insured. The first column reports the moral hazard effect and *t*-statistics (in parenthesis) for the healthy group. The second column reports the difference in moral hazard effects between the two health groups. The final column reports the over identification tests with three degrees of freedom (*p*-values in parenthesis). *** indicates statistical significance at .01 or better. ** indicates statistical significance at .05. * indicates statistical significance at .10.

	Healthy	Sickly-Healthy	*J*-Statistic
H=ILLNESS			
DOCCHRON	1.69***	-0.52*	4.48
	(6.14)	(-1.81)	(0.21)
DOCACUTE	1.74***	-0.19	3.13
	(9.15)	(-0.82)	(0.37)
H=DISABILITY			
DOCCHRON	1.60***	-0.52*	4.45
	(6.06)	(-1.79)	(0.22)
DOCACUTE	1.72***	-0.37	3.22
	(9.20)	(-1.63)	(0.36)
H=DISEASE			
DOCCHRON	1.70***	-0.94***	3.64
	(6.23)	(-3.87)	(0.30)
DOCACUTE	1.76***	-0.64***	4.59
	(9.47)	(-3.47)	(0.20)

11. POLICY IMPLICATIONS

Empirical findings suggest that physician care is not a homogenous good and that the moral hazard in the demand for physician services cannot be easily characterized by a single estimate. One's quantitative characterization depends on the particular condition-specific component of physician services *and* the health group under consideration. Policy that is founded on a moral hazard estimate for physician services as an aggregate entity and then applied to particular health groups and condition-specific components may produce undesired outcomes. In fact, as a consequence of the empirical findings, theories of health insurance design discussed above would argue that moral hazard is more of a problem for the healthy for chronic condition related physician visits. Thus, keeping risk premium across health groups constant, higher cost sharing should be imposed for the healthy for this service

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category.[21] On the other hand, differential cost sharing across health groups may not be necessary for acute condition related physician visits, since, taken together, the results do not support an appreciable difference in moral hazard effects between the health groups for this service category.

One possible concern with the recommendation that physician visits should have cost sharing varying with health status is that differentiating individuals by health status may lack practical relevance since it may not be accurately measured by the insurer. Individual clinical characteristics would need to be reviewed by health insurers to determine cost sharing in a similar way that they currently use utilization reviews to determine whether a particular individual will have coverage. However, electronic medical records and health assessment data, which are increasingly available as part of disease management programs, might overcome this issue over time [Chernew *et al*. (2007)]. Finally, in some cases, "disease staging" may allow insurers to identify individuals [Chernew *et al*. (2000)] with chronic diseases too mild to be candidates for the higher cost sharing.

Optimal health insurance in the multi medical service context should take into account whether a particular type of care produces cost effects [Goldman and Philipson (2007)]. For example, prescription drugs may be optimally subsidized more for patients with chronic diseases since use of these drugs could lower future medical expenditures. Incorporating the offset effects into the policy analysis of the moral hazard effect estimates requires estimates of the effect of a change in copays for physician visits (especially for visits associated with chronic conditions) on future hospital costs. Unfortunately, we neither have information on copays nor a panel data to accomplish such a task. *However*, empirical evidence gathered so far suggests no or little offset effects for the healthy and large offset effects for the sickest individuals [Chandra *et al*. (2010), see Remler and Greene (2009) for an excellent review of the literature]. Thus, with the likely little or no offset effects for the relatively healthy and large offset effects for the relatively sickly, our conclusion that cost sharing for the healthy should be higher than that for the sickly for chronic condition related physician visits becomes a conservative comparison and should remain intact. This is because with the likely large offset effects for the sickly, the optimal cost sharing for the sickly would have been lower than what

[21] Following Pauly and Blavin (2008), we assume that the variance of expenditures is the same across health groups within a service, so that the marginal risk avoidance value associated with changes in cost sharing is the same across health groups within a service.

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our moral hazard effect estimates would have predicted had we quantified the optimal cost sharing for this health group.[22]

CONCLUSIONS

This paper analyzes the extent to which moral hazard varies by the health status of the individual and the type of medical condition associated with the visit. The paper also explores whether optimal cost sharing in health insurance should be based on the health status of the insured and whether this health-specific cost sharing depends on the type of medical condition being treated. The results indicate that the moral hazard effect is higher for the healthy for chronic condition related physician visits. The results, on the other hand, do not support an appreciable difference in moral hazard effects between the healthy and sickly groups for acute condition related physician visits. The findings furthermore indicate that it is wise to account for the possibility that health insurance is endogenous to medical services demand. Exogeneity of insurance is rejected in the demand for all physician services. And this endogeneity matters. Comparison of the correctly specified GMM model formulation results with those emanating from the Negative Binomial specification shows that the moral hazard estimates are sharply understated if the endogeneity is ignored. The findings suggest that optimal health insurance should be designed to have differential cost sharing that varies across the health status of the insured *and* the medical condition associated with the visit rather than to have uniform cost sharing. In particular, the results suggest that cost sharing should be higher for the healthy for chronic condition related physician visits, whereas health-specific cost sharing may not be necessary for acute condition related physician visits. This paper analyzed moral hazard effects for physician visits by type of medical condition, i.e., groups of diseases such as chronic and acute. Future work may analyze the moral hazard effects in the demand for disaggregated physician visits by disease type, such as cancer, heart disease, diabetes, etc.

Appendix: Demand for Physician Visits by Type of Medical Condition

This table presents the coefficient estimates and *t*-statistics (in parenthesis) estimated using the Generalized Method of Moments (GMM) method for the following regression model:

$$y = \exp(X\beta + PRIVATE\delta_1 + PRIVATE * H\delta_2)\nu + \tau,$$

[22] Please note that we do not make quantitative predictions about the sizes of optimal cost sharing across health groups but instead discuss relative comparisons of the sizes of optimal cost sharing across health groups.

where y is a condition-specific physician visits category, ν is the interpersonal heterogeneity component and τ is a regression specification error. To implement the GMM estimation, a probit model is estimated for the presence of private health insurance and predicted probabilities $\hat{\Phi}$ are obtained. $Z_1 = (\text{SELF-EMP}, \text{FIRMSIZE}, \text{UNION})$ is the vector of identifying instruments. GMM estimation is performed using $Z = (X, \hat{\Phi}, \hat{\Phi} * H, Z_1)$ as instruments. The standard errors are robust to the presence of heteroskedasticity. *** indicates statistical significance at .01 or better. ** indicates statistical significance at .05. * indicates statistical significance at .10.

	H=ILLNESS		***H=DISABILITY***		***H=DISEASE***	
	DOCCHRON	**DOCACUTE**	**DOCCHRON**	**DOCACUTE**	**DOCCHRON**	**DOCACUTE**
PRIVATE	1.48***	1.62***	1.45***	1.69***	1.42***	1.77***
	(5.28)	(7.76)	(5.24)	(7.75)	(4.98)	(7.86)
PRIVATE*H	-0.47**	0.15	-0.66***	-0.002	-0.41**	-0.27*
	(-2.54)	(0.78)	(-3.53)	(-0.01)	(-2.42)	(-1.90)
PUBLIC	1.19***	1.23***	1.10***	1.24***	1.15***	1.21***
	(6.86)	(10.50)	(6.25)	(9.94)	(6.84)	(10.16)
MIDWEST	-0.18*	-0.15**	-0.16	-0.16**	-0.18*	-0.15**
	(-1.65)	(-2.27)	(-1.54)	(-2.30)	(-1.68)	(-2.18)
SOUTH	-0.007	-0.09	-0.007	-0.09	-0.007	-0.08
	(-0.06)	(-1.28)	(-0.06)	(-1.23)	(-0.07)	(-1.13)
WEST	-0.41***	-0.14*	-0.39***	-0.14*	-0.40***	-0.13*
	(-3.54)	(-1.86)	(-3.42)	(-1.81)	(-3.49)	(-1.80)
URBAN	-0.17**	-0.07	-0.15**	-0.07	-0.17**	-0.06
	(-2.18)	(-1.51)	(-2.04)	(-1.46)	(-2.22)	(-1.24)
AGE	0.06***	0.04***	0.05***	0.04***	0.05***	0.03***
	(2.95)	(3.07)	(2.73)	(2.94)	(2.83)	(2.70)
AGE2	-0.36	-0.49***	-0.30	-0.48***	-0.33	-0.43***
	(-1.61)	(-3.20)	(-1.37)	(-3.06)	(-1.50)	(-2.81)
MALE	-0.46***	-0.56***	-0.48***	-0.56***	-0.46***	-0.56***
	(-7.63)	(-12.51)	(-7.91)	(-12.15)	(-7.85)	(-12.49)
WHITE	0.23***	0.41***	0.24***	0.42***	0.22**	0.42***
	(2.62)	(7.39)	(2.74)	(7.41)	(2.48)	(7.50)
MARRIED	-0.14*	-0.02	-0.11	-0.03	-0.12*	-0.02
	(-1.84)	(-0.46)	(-1.53)	(-0.50)	(-1.66)	(-0.44)
COLLEGE	0.18***	0.12**	0.19***	0.11**	0.20***	0.11**
	(2.78)	(2.56)	(2.82)	(2.40)	(3.01)	(2.41)
INCOME	0.002***	0.002***	0.002**	0.002***	0.003***	0.002***
	(2.62)	(3.17)	(2.54)	(2.96)	(2.96)	(3.02)
EMPLOYED	-0.30***	-0.06	-0.28***	-0.06	-0.31***	-0.05
	(-3.23)	(-0.99)	(-3.01)	(-0.91)	(-3.45)	(-0.83)
SICKPAY	-0.008	-0.20**	0.008	-0.21**	0.06	-0.20**
	(-0.06)	(-2.32)	(0.07)	(-2.34)	(0.53)	(-2.28)
ILLNESS	1.20***	0.45***	0.93***	0.51***	0.93***	0.50***
	(8.56)	(4.12)	(14.95)	(7.94)	(14.67)	(7.95)
DISABILITY	0.61***	0.50***	1.00***	0.51***	0.63***	0.50***
	(9.62)	(8.63)	(6.83)	(4.29)	(9.74)	(8.64)
DISEASE	1.46***	0.62***	1.48***	0.62***	1.73***	0.77***
	(24.77)	(13.97)	(24.91)	(13.86)	(13.15)	(7.49)

CONSTANT	-3.87***	-2.21***	-3.82***	-2.24***	-3.79***	-2.24***
	(-8.56)	(-7.84)	(-8.43)	(-7.69)	(-8.55)	(-7.88)

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