Qualitative differences in the moral hazard effect of health insurance across medical services

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Abstract

I introduce a new perspective in considering the traditional moral hazard effect (the price effect) of health insurance across several medical services. I consider a new effect of health insurance on the decision to become a potential health care customer, and separate this effect from the traditional moral hazard effect. While this new effect is prevalent in general practitioner visits and hospital stays, the traditional moral hazard effect prevails in specialist visits and operations. In public insurance for hospital stays and in overall physician visits I identify and quantify both effects simultaneously. These qualitative differences suggest different policy measures in healing moral hazard.

1 Introduction

"Refuse to be ill. Never tell people you are ill; never own it to yourself. Illness is one of those things which a man should resist on principle."

Edward George Bulwer-Lytton

Popular portal services such as drkoop.com, webmd.com and intellihealth.com provide online health-related information. As a common feature of these web sites "self-care advisors" or "experts" provide "consumer-focused" health care information. The advice given by these experts consist of a few paragraphs, usually starting with several reassuring statements, and going through various home remedies. Then the final paragraph generally contains a conditional sentence that starts, "You should visit the doctor if...". Such paragraphs usually specify conditions whose urgency is presumably obvious to many of the readers. Although there are a variety of disclaimers in all these web sites, a report in the U.S. Food and Drug Administration Consumer Magazine (June 1996, revised in 1998) indicates that consumers are showing a growing interest in obtaining information about health as a means of supplementing traditional medical counsel.

Whether the utilization of these online services, particularly using the services of "self-care advisors", decrease the utilization of medical services, at least for non-complicated medical conditions, is an open empirical question. But a related observation, that some major health insurance companies are partners with some of these online portals suggests so. For example, Humana and WebMD, Aetna and Intellihealth are partners (Aetna actually owns Intellihealth). A possible reason that causes health insurance companies and these online services to be partners is the cost-savings for the insurance companies due to decreased health care demand of their customers. While the (especially the recurrent) users of these web sites possibly self-select to use the online services due to having minor conditions, they might still have chosen to visit a doctor had the reassurance available from the online services not existed.

Note that once a decision to visit a doctor has been made by an individual, the number of actual visits is unlikely to depend on the information presented in the online portal any more. Then the quantity demanded is determined by, as argued in Cameron et al. (1988), consumer attributes, purchasing power and the health status. Furthermore, the doctor is also involved in the decision as argued by Pohlmeijer and Ulrich (1995). So at what stage do the health insurance companies think that online portals can affect the demand for health care? Probably during the formation of the perception of the need to demand health care. Then it follows that the threshold to make a decision to demand health care is endogenous, and hence it can be affected from a variety of factors, such as having access to the information presented in the online portals.

Early in the literature Pauly (1968) recognizes that having health insurance may decrease preventive activities, and hence increase the likelihood of a sickness. This effect is called the ex ante moral hazard effect by Zweifel and Manning (2000), since it occurs prior to the sickness. Sickness is the main reason to form a decision to demand health care. However, whether a consumer perceives a given level of sickness serious so to decide to demand health care may be affected by other factors, such as the reassurance from the online portals. Similar to the reassuring information from the portals, a reassurance due to having health insurance might also affect this perception. That is, even if one controls for the health status, having health insurance may decrease the threshold of making a decision to demand health care, and this has never been investigated in the literature. Having health insurance may make it easier for one to decide that he/she needs medical care. In this paper, I consider this effect of health insurance on the decision threshold a different type of moral hazard, and identify it separately from the traditional moral hazard effect, that is, the usual price effect of health insurance. I call this new type of moral hazard MH1 in short.

The price effect of health insurance (I call it MH2), on the other hand, has received considerable attention since Pauly (1968). Craig, Dusansky and Koç (2001) (henceforth CDK) has a concise survey of the relevant papers. To explain MH2, Pauly (1968) considers two demand regimes D_1 and D_2, where D_1 is the ex ante demand regime that always yields the outcome zero, and D_2 is the ex post demand regime, which is a usual downward sloping demand curve. He argues that the individual switches from D_1 to D_2 with a given probability of sickness. Pauly (1968) acknowledges that this probability may change depending on the level of the individual's self-preventive activities, but he abstracts from this effect. Thus, more generally, by assuming the randomness of the switching probability between D_1 and D_2, Pauly (1968) abstracts from MH1, and concentrates on MH2.

In the present paper, the probability of switching between D_1 and D_2 does not only depend on the occurrence of a sickness. More generally, I consider this probability as the probability of perceiving a need to demand health care. As suggested by the collaboration of the health insurance companies and the online portals, the perceived threshold level of deciding to demand health care is subjective. Then, just like the demand for health care, factors other than the health status, such as, having health insurance and other personal attributes are likely to play a role in the formation of such a perception. An increase in this probability of switching from D_1 to D_2 due to MH1 results in incurring the losses related to MH2 more frequently, thereby contributing to welfare loss related to MH2. This broader effect of health insurance on the probability of switch (MH1) is the main focus of the present paper.

My results suggest an early indication of qualitative differences in the effect of health insurance across medical services. Different types of insurances display different compositions of MH1 and MH2 effects depending on the medical service considered. For private insurance, the MH1 effect is indicated in the case of medical doctor visits, in particular for general practitioner visits excluding specialists, and in the case of hospital visits. That is, having health insurance makes the decision to demand medical services from a general practitioners and hospitals easier. There is strong evidence of MH2 in the demand for physicians through specialist visits and also in the demand for operations. Thus, in the case of general practitioner visits (or hospital stays) the effect of having health insurance on developing an intention to demand health care is more important than the price effect of health insurance. In the demand for specialist services and operations, the price effect (MH2) is dominant. Note that for private insurance, either MH1 or MH2 is significant in any one of the medical services, so there is no simultaneous identification. However, in public insurance MH1 and MH2 are both significant in the case of hospital stays, leading to simultaneous identification. Other results related to public insurance are parallel to the case of private insurance, but the moral hazard effect is more intense.

These results point out that the approach that considers the moral hazard effect only as the price effect of health insurance across the medical services has to be refined. The identification of different types of moral hazard effects suggest qualitative differences between the effects of health insurance on the demand across medical services. While a high co-pay in the case of specialist visits seems like an appropriate remedy to the moral hazard effect, intense educational activities for conditions thet lead to general practitioner visits and hospital visits, such as the online portals, 24 hour telephone lines operated by insurance companies may be preferable.

The issues of the decision model that underlies the formation of demand, possible endogeneity of health insurance (adverse selection) and the economic identification are discussed in Section 2. Section 3 presents the econometric methodology used in this paper. Section 4 presents the data used. Section 5 discusses the estimation results and Section 6 concludes.

2 The decision model and the empirical strategy

Health care demand can be measured by frequencies of visits, for example, the number of visits to a doctor in a given period. In general the outcome zero is observed in high frequencies in the data sets related to health care demand, and this is the case in the data set that I use as well. Poisson distribution does not explain the excess number of zeros successfully in most data sets, including the present one. Negative Binomial (NB) distribution is a plausible alternative to account for extra zeros that also accounts for individual heterogeneity, but it does not account a two-part decision process that is more appropriate to capture the differing roles of health insurance both in the stage of formation of the perception to demand health care and in the stage of the formation of the actual demand. More precisely, I assume that an individual makes his/her demand decision in two stages:

Stage 1: Decide whether to become a potential health care customer (PHCC), i.e., determine the demand regime: D_1 or D_2, where $D_1 = 0$.

Stage 2: Decide how much health care to demand, i.e., the actual quantity demanded at D_2, where $D_2 \geq 0$.

In the first decision stage (Stage 1) if the individual chooses D_1, then his demand is unambiguously zero. In any period that the individual switches to D_2, he becomes a potential health care customer (PHCC), and decides how much health care to demand (Stage 2). The actual demand in D_2, measured by, say, the number of doctor visits, may as well be zero due to, for example, financial constraints. So an observed outcome of zero health care demand may come from two different regimes, but just from which regime may not be observable.

The decision stages such as the above introduce other plausible sources to the outcome zero, and hence are more successful than Poisson and NB in explaining health care demand. Zero-inflated (ZI) regression models introduced by Lambert (1992) account for a two-part decision process as described above, and they can account for more zeroes than the Negative Binomial when necessary. The ZI regression model involves parametrizations of both the mean in D_2 and the probability of switching from D_1 to D_2. I discuss the ZI model in more detail in the next section. Now I turn to a general discussion of the moral hazard estimations in the literature and how they relate to the present paper.

The basic regime for the existing health care demand estimations in the literature is D_2. The presumably positive coefficient of health insurance identifies MH2 in such estimations. Note that with this approach only MH2 can be identified as in Windmeijer and Santos-Silva (1997) and CDK (2001a,b). The present paper, however, attempts to separately identify MH1 and MH2 using the ZI regression model, and the decision stages above also serve this purpose.

To identify the MH1 effect of health insurance on the switching probability the coefficient of the health insurance dummy in this probability of switch is used. I also use the other determinants of health care demand also as the determinants of the switching probability between the regimes. That is, the probability of switching is determined by not only the health status and the health insurance, but also by the personal attributes and the purchasing power, including the health insurance dummy. The purpose of using identical determinants is to identify (possibly conflicting) roles of determinants in the switching probability and the ex post demand of a PHCC. The inclusion of health status as a determinant of the probability of switch controls for the health status, and allows me to abstract from the ex ante moral hazard effect.

When the health care demand is estimated with a ZI model, MH1 is indicated if having health insurance increases the probability of switching from D_1 to D_2. Insurance can also increase the demand of a PHCC, and this can empirically be identified separately as MH2. Thus, such an estimation provides evidence on the decomposition of moral hazard into two categories in terms of the underlying incentives, which is the primary goal of this paper. Then, I present the relative prevalence of each of these categories across medical services, leading to subsequent policy implications.

These results suggest an early indication of MH1. One potential concern may arise concerning the endogeneity of the health insurance variable in the estimation of health care demand. Unobservable heterogeneities of consumers can be correlated with the the health insurance dummy, causing endogenous regressors problem. CDK (2001a) show that endogeneity is a problem only in the case of specialist visits using the same data set. Based on this result, my results would be valid for other medical services, but in specialist visits, the quantities have to be evaluated with some caution. In the literature, there does not exist an exact solution for endogenous regressors problem in the case of Zero-inflated models (Greene's (1994) solution is a rough approximation). Furthermore, I am interested in the quantitative differences in th effect of health insurance across the medical services. So it is reasonable to try to identify both types without solving for endogeneity, at least in the first pass.

Another concern is the possibility that the identification may be due to the functional form I use, which is the Zero-inflated Negative Binomial. Apart from the tests conducted between various functional forms, usage of ZINB can be defended on a variety of grounds. First, the negative binomial distribution is argued to be appropriate to model health care demand in D_2, due to at least one of the processes that underlie it. The process of interest accounts for contagion (thus interdependence) between time intervals, much like illness spells that cause multiple visits (see Cameron et al. (1988) and Cameron and Trivedi (1999)). Second, post-estimation analysis indicates that the part of the sample that is unlikely to be a PHCC is indeed very healthy relative to the whole population, they are younger, richer and more likely to be males. Thus the identification makes economic sense. Finally, the ratio of zeros in general practitioner, specialist and hospital services is approximately the same (%95), but still I observe both types of moral hazard in the demand for at least one medical service, and also, in hospital visits, both effects are separately identified.

3 Econometric method

In general, finite mixture models are appropriate when it is possible that the same outcome can arise from more than one processes. In the present application D_1 always yields the outcome zero, and D_2 yields a non-negative integer. This can be analyzed best via a special case of finite mixture models, the Zero-Inflated (ZI) regression model.

Estimating a ZI regression model involves estimating the switching probability between the regimes using the logit regression model,[1] and estimating the second regime

[1]Using probit or Prentice's F distribution, which is a generalization of the logistic distribution (see Cameron and Trivedi (1998)), are other possibilities but logit is more commonly used, and my results are robust to using Probit.

by any non-degenerate count-data regression model. Poisson or Negative Binomial Regression models are by far the only count-data models used for the purpose of estimating the second regime, rendering Zero-Inflated Poisson (ZIP) and Zero-Inflated Negative Binomial (ZINB) models, respectively.[2] Thus, one can analyze the effect of an independent variable in different decision stages, on the assumption that it plays a role in switching between these underlying regimes. Technically, the choice of covariates for the switching probability (Stage 1) is completely independent from the choice of covariates for the ex post demand D_2 (Stage 2). However, using the same covariates in both parametrizations serves the purpose of identifying the possibly different roles of the same determinant in each stage. In this paper, I use identical sets of determinants both for the switching probability between D_1 and D_2, and for the demand in D_2.

The basic distribution underlying the Zero-Inflated regression model is:

$$\begin{aligned} y_i = 0 &\quad \text{with probability } P(\mathrm{D}_1) \\ y_i \sim \text{Poisson}[\alpha_i] &\quad \text{with probability } P(\mathrm{D}_2) \end{aligned}$$

where $P(\mathrm{D}_1)+P(\mathrm{D}_2)=1$, and Lambert (1992) proposes to estimate $P(\mathrm{D}_1)$ by using either of the logit or probit models and employing the Poisson (or any other count-

[2]Extending ZIP and ZINB to, respectively, ZIP-Hurdle and ZINB-Hurdle models are also possible (provided identification is achieved). Hurdle models are count data models that assume a nonlinearity in the process, and hence let the zero outcome come from a different distribution than the distribution of the positive outcomes. Using a Hurdle model, doctor-induced moral hazard can be accounted for, as in Pohlmeijer and Ulrich (1995). Note that in a Hurdle model, zero need not necessarily be the "Hurdle", for example, as suggested by Wilson (1998), a positive hurdle in a Hurdle model is conceivable.

data) regression model for estimating the coefficients in D_2. That is, letting $F(\cdot)$ be the logistic distribution, Zero-Inflated Poisson (ZIP) model is given as:

$$P(\mathrm{D}_1) = F(Z, \gamma)$$

$$P(y_i = j|\mathrm{D}_2) = \frac{exp(-\lambda_i)\lambda_i^j}{j!} \qquad j = 0, 1, 2, ...$$

where $\lambda_i = e^{X_i\beta}$ as in all the familiar count models. Even though $P(\mathrm{D}_1)$ is parametrized, the marginal effects on the probability of switch, that is, $P(\mathrm{D}_2)$ is straightforward since, $P(\mathrm{D}_2) = 1 - P(\mathrm{D}_1)$.

In the present application, $F(Z, \gamma) = F(Z\gamma)$ and $F(\cdot)$ are the cumulative probability function of the logistic distribution. Also the same determinants are used for both parametrizations, that is, X and Z will be identical. Now I proceed to the ZINB regression model.

The two models ZIP and ZINB have no technical difference except that the decision in Stage 2 is parametrized by NB distribution in the case of ZINB (Greene, 1994), that is,

$$P(\mathrm{D}_1) = F(Z, \gamma) = F(Z\gamma)$$

$$P(y_i = j|\mathrm{D}_2) = \frac{\Gamma(j+\alpha^{-1})}{\Gamma(j+1)\Gamma(\alpha^{-1})}(\frac{\alpha^{-1}}{\alpha^{-1}+\mu})^{\alpha^{-1}}(\frac{\mu}{\alpha^{-1}+\mu})^{j}.$$

where, j is a non-negative integer and α is a non-negative real number, and $F(\cdot)$ is the logistic distribution in the present application. The NB distribution reduces to Poisson when $\alpha = 0$, so ZIP is nested in ZINB, which makes the likelihood ratio test applicable. For the gradients of the likelihood function, I refer the reader to Greene (1994).

The ZINB estimation results a coefficient for each covariate for each decision stage. If $X = Z$ as in my case, then there are two coefficients for each covariate, one for Stage 1 and the other for Stage 2. These two coefficients allow to differentiate between the roles of the same covariate in different decision stages. In the case of health insurance dummies, this enables me to differentiate between the types of moral hazard effects.

Marginal Effects in ZI models are not trivial but relatively straightforward. For the sake of completeness and clarity of exposition they are given here. The mean of ZIP and ZINB are the same and given by:

$$E(Y|X,Z) = (1-F)\lambda$$

where $\lambda = e^{X\beta}$ and $F = F(Z,\gamma) = F(Z\gamma)$. Thus the marginal effect of X_i is

$$\frac{\partial E(Y|X,Z)}{\partial X_i} = \frac{\partial}{\partial X_i}[(1 - F(Z\gamma))e^{X\beta}]$$

Consider the following two cases. In the first case, the covariate X_i is a regressor in both of the stages. In the second case, it is a regressor in only one stage. These two cases lead to different marginal effects. In the present application Case 1 holds, and therefore Case 2 is not detailed in what follows.

Case 1: Let the variable X_i be a covariate in both regimes, i.e., $\exists i$ such that $X_i = Z_i$. Then

$$\frac{\partial E(Y|X,Z)}{\partial X_i} = -\gamma_i F'(Z\gamma)e^{X\beta} + (1 - F(Z\gamma))\beta_i e^{X\beta}$$

The first part, i.e., $-\gamma_i F'(Z\gamma)e^{X\beta}$ is the marginal effect in Stage 1 and the second part, i.e., $(1 - F(Z\gamma))\beta_i e^{X\beta}$ is the marginal effect in Stage 2. Since F', $1 - F$, and $e^{X\beta}$ are all positive, the marginal effect in the first stage (the marginal effect on probability of switching to D_2) has the opposite sign with the estimated coefficient γ_i, whereas the marginal effect in the second stage, has the same sign with the estimated coefficient β_i. The sign of the overall marginal effect differs depending on signs and ratios of the coefficients with respect to the hazard function associated with the logistic density.

Define this hazard function by

$$\frac{F'(Z\gamma)}{1 - F(Z\gamma)} = h(Z\gamma)$$

Note that since logistic distribution is used, $F(Z\gamma) = \frac{exp(Z\gamma)}{1+exp(Z\gamma)}$, the hazard function coincides with the cumulative density function, that is, $h(Z\gamma) = F(Z\gamma)$. The sign of the Overall Marginal Effect (OME) can be given as:

Case 1.1. $(\beta_i, \gamma_i > 0)$. OME > 0 iff $\frac{\beta_i}{\gamma_i} > h(Z\gamma)$.

Case 1.2. $(\beta_i, \gamma_i < 0)$. OME > 0 iff $\frac{\beta_i}{\gamma_i} < h(Z\gamma)$.

Case 1.3. $(\beta_i > 0, \gamma_i < 0)$. OME > 0.

Case 1.4. $(\beta_i < 0, \gamma_i > 0)$. OME < 0.

In this case, the percentage change in the dependent variable as a result of a marginal change in a given independent variable X_i is (note that $X = Z$ in the present application)

$$\frac{\frac{\partial E(Y|X)}{\partial X_i}}{E(Y|X,Z)} = \beta_i - h(Z\gamma)\gamma_i = \beta_i - F(Z\gamma)\gamma_i.$$

Case 2: Now consider a variable X_i that is used as a covariate in only Stage 2, that is, $X_i \epsilon (X \backslash Z)$. Then the marginal effects and percentage changes can easily be found by directly following the steps in Case 1.

In ZIP or ZINB, when the same covariates are used for both decision stages, as in the present application, the estimated percentage changes in the dependent variable (evaluated at the sample mean) as a function of a given covariate is given as

$$\hat{\beta}_i - h(\bar{Z}\hat{\gamma})\hat{\gamma}_i \tag{1}$$

where $\hat{\beta}_i$ is the estimated coefficient of Z_i in Stage 2 and γ_i is the estimated coefficient of Z_i in Stage 1, and $\bar{Z}$ is the vector of means of Z_i's.

4 The data

The data set is from the 1993 National Health Interview Survey and its Health Insurance Supplement Survey compiled by the US Department of Health and Human Services. It is the same data set used in CDK (2001a,b) and Craig and Koç (2001). The sample consists of 18,116 adults between the ages of 18 and 64. The insurance supplement is available only for the 3^{rd} and 4^{th} quarters therefore the starting data set consists of 37,225 individual records. 11,412 observations contain veterans, but these observations are removed since their medical care demand and access to medical care are different from the general population (see Wilson, 1998). In addition, 7,684 more observations are removed due to incomplete responses, and 13 are removed due to inconsistent results.[3]

Each observation consists of 33 variables relevant to medical service demand or the probability of switching from D_1 to D_2. Table 1 lays out the definitions of the

[3]The removal of all the above does not substantially alter the mean and the standard deviation of the variables.

Table 1: The Independent variables.

Variable	**Description of Variable**
sex	1 if male
age	Number of years old
age^2	Age squared divided by 1000
white	1 if white
imm	1 if born outside of the United States
mar	1 if married
nhs	1 if no high school (h.s.)diploma
univ	1 if h.s. graduate and some years beyond h.s.
rgn1	1 if resides in the Northwest
rgn2	1 if resides in the Midwest
rgn3	1 if resides in the South
rgn4	1 if resides in the West
famsz	Number of family members
city	Metropolitan Statistical Area in excess of 100,000
inc	Estimated family income
pubins	1 if publicly insured
privins	1 if privately insured
emp1	1 if employed in the public sector
emp2	1 if employed in the private sector
offer	1 if a family member is offered private insurance by an employer
disease	if one or more chronic conditions
illness	if poor or fair health
disable	1 if limited in activity
h1	1 if disease, illness and disable
h2	1 if disease, no illness and disable
h3	1 if disease, illness and no disable
h4	1 if no disease, illness and no disable
h5	1 if disease, no illness and no disable
h6	1 if no disease, no illness and no disable
limdy	Number of restricted activity days over the last two weeks

independent variables, and the corresponding summary statistics are given in Table 2. These independent variables are classified into three groups, and the groups are separated from each other via horizontal straight lines. The first fourteen rows give the definitions of the variables that are related to the personal attributes of the consumer such as sex, age, race etc. Consumer's personal attributes affect the health care demand or the switching probability through preferences and risk factors. The next seven rows define the variables that affect the individual's ability to pay for the medical services, such as income, employment, public and private insurance.[4] These variables may also affect the switching probability, since they not only constitute the outside option, but also affect the well-being of a person and hence decrease the frequency of illness spells.

A more detailed analysis of individual incentives requires a more disaggregation on the part of the insurance dummy both with respect to types like HMO, PPO, FFS and POS, and with respect to the coinsurance rates within these types, as well as the different incentive structures. Baker and Royalty (2000) presents an example where changes in the incentive structure cause changes in health care demand. Medical Expenditure Panel Survey has some of these details, but for my purposes using a private and a public insurance dummy is sufficient.

The last group in Table 5 consists of the remaining last 10 rows. The variables in this group are the health-related determinants of health care demand. A classification of health status in rows 25-31 is given as H1 through H6. This classification is constructed from the data set based on definitions of the three dimensions of health:

[4] The income variable is achieved by transforming the interval responses to point estimations. The details of the technique used is available upon request.

Table 2: Descriptive Statistics: Independent Variables.

Var.	Obs.	Mean	St.Dev.	Min	Max
sex	18116	.45	.50	0	1
age	18116	36.94	11.32	18	64
age^2	18116	1.49	.90	.32	4.10
white	18116	.80	.40	0	1
imm	18116	.13	.34	0	1
mar	18116	.64	.48	0	1
nhs	18116	.16	.37	0	1
univ	18116	.47	.50	0	1
rgn2	18116	.26	.44	0	1
rgn3	18116	.31	.46	0	1
rgn4	18116	.22	.42	0	1
famsz	18116	3.00	1.49	1	10
city	18116	.76	.43	0	1
inc	18116	46.68	39.32	0.79	111.34
pubins	18116	.08	.28	0	1
privins	18116	.74	.44	0	1
emp1	18116	.11	.32	0	1
emp2	18116	.64	.48	0	1
offer	18116	.89	.32	0	1
h1	18116	.06	.23	0	1
h2	18116	.08	.14	0	1
h3	18116	.02	.14	0	1
h4	18116	.02	.15	0	1
h5	18116	.21	.40	0	1
limdy	18116	.60	2.33	0	14

Table 3: The dependent variables.

Variable	**Description of Variable**
MDMS	Number of visits with a physician over the last two weeks
GPMS	Number of visits with a general practitioner over the last two weeks
SPMS	Number of visits with a specialist over the last two weeks
HOSP	Number of nights in a short-stay hospital over the last year
OPER	Number of operations over the last year

disease, illness and disability. Initially, for each of these three dimensions a dummy variable is constructed. *Disease*, the state when something objectively and demonstratively went wrong in the mechanics of the organism, is identified by the presence of chronic conditions. *Illness*, the state that is known to follow 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. *Disability*, the final component of health, is the loss of opportunity imposed by social and environmental factors on people with impairments relative to the perceived norm of hindrance. The presence of disability is based on activity limitation status. According to these definitions, disability is a subset of disease. Then, the combinations of these three indicators variables separate the sample into six disjoint health cohorts, H1-H6. Thus, concerns about multicollinearity between disease, illness and disability no longer exist. The total restricted activity days in the past two weeks, LIMDY, is included as a health variable to account for within-cohort variation caused by acute conditions.

Table 3 presents the dependent variables that are five counts of medical services. Table 4 and Table 5 gives the related summary statistics and a comparison of the Poisson-predicted proportion of zeroes with the actual proportion of the zeroes in the data set, respectively.

Table 4: Descriptive Statistics: Dependent Variables.

Var.	Obs.	Mean	St.Dev.	Min	Max
MDMS	18116	.13	.44	0	10
GPMS	18116	.06	.28	0	6
SPMS	18116	.07	.34	0	9
HOSP	18116	.39	2.39	0	62
OPER	18116	.06	.28	0	4

Table 5: Predicted and actual proportions of zero outcome.

Variable	Poisson-predicted Proportion of Zeros	Actual Proportion of Zeros
MDMS	% 88.12	% 90.08
GPMS	% 94.39	% 95.07
SPMS	% 93.35	% 94.64
HOSP	% 67.44	% 92.48
OPER	% 94.05	% 94.70

Two of the dependent variables are counts of hospital services over the last year: operations (OPER) and nights spent in the hospital (HOSP). The OPER count excludes pregnancy related operations, therapeutic and diagnostic non-operative procedures. HOSP contains only visits to non-military, short-stay hospitals, since individuals with access to military facilities are removed. The last three dependent variables are counts of physician services over the past two weeks: visits with a physician (MDMS, where MS is the abbreviation of medical services throughout this paper), visits with a specialist (SPMS) and visits with a general practitioner (GPMS). MDMS includes only personal consultations with a physician, and MDMS is the sum of GPMS and SPMS. These consultations may be conducted in a home, clinic or office, but not in a laboratory.[5] This portfolio of health care covers a significant portion of the medical care industry, but it abstracts from psychiatric, dental, cosmetic and pharmaceutical demand as well

[5]GPMS may be interpreted as the utilization of primary care, while SPMS is the utilization of medical services that involve specialized clinical expertise.

as home care and alternative medicine.

5 Estimation and Results

To check the appropriateness of the assumption of two regimes, and to check for the existence of individual heterogeneity, estimations of Poisson, NB, ZIP and ZINB models and tests between them have been performed.[6] Table 6 provides the results of tests among Poisson, NB, ZIP and ZINB models. The first column lists the dependent variables, the second, third and fourth columns provide the test result between ZIP and Poisson models (Vuong (1989)), ZINB and ZIP models (LR test), and ZINB and NB models (Vuong (1989)), respectively. The model favored by the test is entered in the appropriate box. The tests favor ZINB to both ZIP and NB throughout all the medical services, both in the case of logit and probit specifications of the switching probability. ZIP is also favored to Poisson. All the tests pass with over % 99.99 significance, so it is rather safe to conclude that ZINB will also be preferred to Poisson. Selection of ZINB in these tests suggest the existence of two demand regimes and two related decision stages as well as individual heterogeneity.[7]

[6]All the estimations are performed by Stata-7.0. In an earlier version of this paper, the programs by Jesper Sorensen that compute ZIP and ZINB using Stata-5.0 are used.

[7]As noted by Cameron and Trivedi (1998), misrecording, where misrecording is concentrated exclusively in the zero class is a possible justification for usage of ZI models. Some evidence has been reported (see Cameron and Trivedi (1998)) with regard to measurement errors in especially in self-reported health care demand data like the present data set. However, they pertain to longer periods than the present data set in the cases of MDMS, GPMS and SPMS and since there is no evidence in the case of operations and it is rather safe to assume that misrecording would be negligible, if any, in these cases. With regard to hospitalizations, there is evidence of underreporting but not necessarily a concentration on zero. In addition, the present data set is different in the sense that it contains the number of overnight stays in hospitals.

Table 6: Tests between various models

Dependent variable **Tests**	**ZIP vs Poisson** **Vuong (1989)**	**ZINB vs ZIP** **LR**	**ZINB vs NB** **Vuong (1989)**
MDMS	ZIP	ZINB	ZINB
GPMS	ZIP	ZINB	ZINB
SPMS	ZIP	ZINB	ZINB
HOSP	ZIP	ZINB	ZINB
OPER	ZIP	ZINB	ZINB

Another concern is whether the identification achieved is functional or economical. There are at least two arguments that can defend the economics underlying the results. The first one is the widespread use of negative binomial model. This model is argued to be appropriate for health care demand due to at least one of the processes that underlies it. This process involves contagion, and hence is appropriate for multiple visits due to a given illness spell (see Cameron et al. (1988)). Second argument that defends the economics of the results comes directly from the estimations. The sample can be ordered according to the estimated probability $F(\bar{Z}\hat{\gamma})$, which equals the hazard rate $h(\bar{Z}\hat{\gamma})$, that represents the probability of not becoming a potential health care customer. Then the part of the sample that contributes most to the extra zeros (top %25 of the sample) is singled out, and related summary statistics are presented in Table 7. In Table 7, the first column lists all the independent and dependent variables. The second and third columns (under the heading "All") give the means and standard deviations that are calculated using the whole sample, respectively. The next two columns are constructed using the regression where the dependent variable is MDMS, and similarly the other columns belong to respective medical services. The summary statistics that belong to, say, MDMS, are constructed using the top %25 of the sample, found by ordering the sample according to the $F(\bar{Z}\hat{\gamma})$.

The results in Table 7 show that those that are estimated not to be Potential Health Care Customers, are indeed very healthy and demanded health care less than the average. To see this from Table 7, compare the means of h1, h2,... in the case of the whole sample, and in the case of the top %25 found for each regression. For example, while the mean of h1 is 0.06 in the case of the whole sample, the mean of those who are not supposed to be PHCCs are zero (in two-digit precision) in all the medical services except specialist visits, and .01 in hospital stays. Similarly, one can see that their health care demand is less than the average, and they are mostly males. This part of the sample, is less likely to have public insurance, but with respect to private insurance the results vary. Those who are less likely to be potential health care customers of general practitioners are also less likely to have private health insurance. For the rest of the medical services, the subsample is not too different from the overall sample with respect to having the private insurance. Other results are displayed in Table 7 That this subsample is very healthy builds confidence in my results.

Before presenting the regression results in Tables 8 and 9, I explain how these tables are constructed. Table 9 presents the results of ZINB-logit estimation in Stage 1, that is, $\hat{\gamma}$ and $F(\bar{Z}\hat{\gamma})$. The estimated coefficients ($\hat{\gamma}_i$'s) show the effects of independent variables on the probability of not being a PHCC, that is, the probability of choosing D_1 at Stage 1, which unambiguously yields zero health care demand. Recall that the sign of the ME of a variable disagrees with the sign of its coefficient at Stage 1, as explained in Section 2.

Table 7: The part of the sample that contributes to the extra zeros the most (top %25).

	All		MDMS		GPMS		SPMS		HOSP		OPER	
Var.s	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
sex	0.45	0.50	0.91	0.29	0.78	0.42	0.97	0.17	0.83	0.38	1.00	0.00
age	36.94	11.32	36.45	9.27	35.57	8.85	35.69	9.62	39.48	10.40	32.48	9.04
white	0.80	0.40	0.77	0.42	0.76	0.43	0.81	0.39	0.80	0.40	0.81	0.39
imm	0.13	0.34	0.17	0.37	0.14	0.34	0.16	0.37	0.18	0.38	0.19	0.39
mar	0.64	0.48	0.69	0.46	0.81	0.39	0.66	0.47	0.48	0.50	0.76	0.43
nhs	0.16	0.37	0.13	0.34	0.13	0.33	0.09	0.28	0.15	0.35	0.16	0.36
univ	0.47	0.50	0.47	0.50	0.46	0.50	0.51	0.50	0.47	0.50	0.52	0.50
rgn1	0.20	0.40	0.18	0.38	0.14	0.35	0.20	0.40	0.25	0.43	0.18	0.38
rgn2	0.26	0.44	0.31	0.46	0.33	0.47	0.30	0.46	0.19	0.39	0.28	0.45
rgn3	0.31	0.46	0.33	0.47	0.38	0.48	0.27	0.45	0.26	0.44	0.28	0.45
famsz	3.01	1.49	3.32	1.58	3.54	1.50	3.11	1.54	2.41	1.38	3.41	1.50
city	0.76	0.43	0.73	0.44	0.67	0.47	0.75	0.44	0.77	0.42	0.75	0.44
inc	46.68	39.32	50.11	39.12	45.30	36.89	53.06	40.02	47.65	39.38	49.56	39.50
pubins	0.08	0.28	0.01	0.08	0.01	0.10	0.01	0.08	0.01	0.08	0.03	0.16
privins	0.74	0.44	0.71	0.45	0.67	0.47	0.76	0.43	0.70	0.46	0.74	0.44
emp1	0.11	0.32	0.08	0.27	0.06	0.23	0.10	0.30	0.12	0.33	0.07	0.26
emp2	0.64	0.48	0.84	0.37	0.76	0.42	0.84	0.37	0.80	0.40	0.80	0.40
offer	0.89	0.32	0.91	0.29	0.89	0.32	0.90	0.30	0.84	0.37	0.92	0.28
h1	0.06	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.07	0.00	0.02
h2	0.08	0.27	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.16	0.00	0.05
h3	0.02	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.04
h4	0.02	0.15	0.00	0.01	0.00	0.00	0.00	0.07	0.01	0.09	0.01	0.12
h5	0.21	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.27	0.05	0.21
limdy	0.60	2.34	0.00	0.00	0.00	0.00	0.01	0.10	0.06	0.45	0.09	0.63
mdms	0.13	0.44	0.01	0.12	0.01	0.13	0.02	0.14	0.04	0.22	0.02	0.20
gpms	0.06	0.28	0.01	0.09	0.01	0.08	0.01	0.11	0.02	0.15	0.01	0.13
spms	0.07	0.34	0.01	0.07	0.01	0.10	0.01	0.08	0.01	0.15	0.01	0.15
hosp	0.39	2.39	0.08	0.94	0.09	0.82	0.07	0.90	0.11	1.37	0.08	0.99
oper	0.06	0.28	0.01	0.14	0.02	0.17	0.01	0.11	0.01	0.13	0.01	0.11

Table 9 presents the results of the ZINB-logit ex post demand estimations and hence the estimated coefficient vector is $\hat{\beta}$. The estimated coefficients ($\hat{\beta}_i' s$) show the effects of the respective independent variables on the demand for the health care in the given specification, conditional on being in D_2. The health care demand may be zero or positive at D_2.

The first row of Table 9 shows the estimated hazard function evaluated at the sample mean for each medical service, that is, $h(\bar{Z}\hat{\gamma})$ for each medical service. Since $h(\bar{Z}\hat{\gamma}) = F(\bar{Z}\hat{\gamma})$, these values also equal to the probability of not switching to D_2. For MDMS, GPMS, SPMS and OPER this probability is lower than % 20, whereas it is considerably higher in the case of hospital stays compared to other medical services: %73. In other words, the switching probability, which equals $1 - F(\bar{Z}\hat{\gamma})$, is much lower in the case of hospital stays compared to the other medical services. This may be due to the emergency nature of hospital stays.

In Tables 8 and 9, Rows 16 and 17 provide regression results related to the independent variables PUBINS and PRIVINS. As can be seen from Table 9, both PUBINS and PRIVINS increase the probability of being a PHCC for MDMS, GPMS and HOSP. This provides an early indication of MH1 in these medical services. (Notice the insignificance in the case of specialist visits and operations). In terms of perceiving a need to demand health care, for each type of health insurance, the greatest effect is in the case of HOSP (e.g., a percentage change of .55, in response to an increase in the probability of having public health insurance). There is also a significant effect in the case of GPMS, percentage changes of .08 and .15 in the cases of private and public insurance, respectively. Note that public insurance is more vulnerable to MH1, except the case of OPER, where MH1 is not significant.

When it comes to the results related to the ex post demand, it can be seen from the rows 16 and 17 in Table 8 that, both PUBINS and PRIVINS increase the demand for SPMS, indicating MH2. This is consistent with findings of CDK (2001b). Considering SPMS, an increase in the probability of having public (resp. private) insurance leads to a %.59 (resp. %.54) increase in the ex post demand. In addition, there is strong evidence that MH2 is prevalent in the case of OPER, for both kinds of insurances at varying levels. Considering OPER, an increase in the probability of having public (resp. private) insurance leads to a %.69 (resp. %.35) increase in the ex post demand. For HOSP, there is evidence for MH2 only in the case of public insurance. Since MH1 is strongly indicated in the case of PRIVINS and HOSP in Table 8 this further strengthens the point of this paper that types of moral hazard should be quantitatively

Table 8: The effects of determinants at Stage 1.

Stage 1 ($\hat{\gamma}$)	**MDMS**	**GPMS**	**SPMS**	**HOSP**	**OPER**
$h(\bar{Z}\hat{\gamma})$	.19	.14	.10	.73	.10
sex	1.21***[a]	.70***	1.79***	.84***	19.99
age	.17***	.11*	.16**	.13***	-.10
age^2	-2.00***	-1.43*	-1.87*	-1.39***	.63
white	-.34*	-.43*	-.18	-.04	-.09
imm	.07	-.29	.26	.12	.49
mar	-.33*	.37	-.80***	-.64***	.91***
nhs	-.42*	-.33	-.92**	-.05	.01
univ	-.11	-.02	-.26	-.15*	.41*
rgn1	.07	.03	.07	-.08	-.32
rgn2	.50**	.41	.39	-.34***	.01
rgn3	.33	.34	-.06	-.30***	-.21
famsz	.15**	.10	.09	-.11***	.10
city	-.18	-.26	-.23	-.07	-.27
inc	-.001	-.002	-.0002	.001	-.002
pubins	-1.03***	-.89**	-.76	-.75***	.19
privins	-.52**	-.48*	-.37	-.37***	-.36
emp1	-.02	-.47	.43	.43***	-.58
emp2	.34	-.14	.66*	.39***	-.20
offer	-.36	-.39	-.37	-.33***	.20
h1	-2.90***	-2.88***	-4.24	-1.09***	-2.14***
h2	-2.12***	-2.30***	-2.34***	-.70***	-1.87***
h3	-2.72***	-2.29***	-3.83**	-.94***	-1.47***
h4	-2.04**	-2.68**	-1.20	-.72***	-.53
h5	-2.64***	-2.20***	-3.13***	-.50***	-1.13***
limdy	-3.01***	-2.93***	-.70***	-.11***	-.11***
cons	-1.65*	.82	-1.38	.87**	-13.86

[a]The superscripts *, ** and *** denote % 10, % 5 and % 1 significance, respectively.

Table 9: The effects of determinants at Stage 2.

Stage 2 ($\hat{\beta}$)	**MDMS**	**GPMS**	**SPMS**	**HOSP**	**OPER**
sex	-.13*[a]	-.07	-.11	.26***	1.20***
age	.01	.03	-.02	.02	-.14***
age^2	-.12	-.36	.22	-.18	1.41***
white	-.22***	-.38***	-.07	-.23***	-.06
imm	-.04	-.09	-.11	.08	-.06
mar	.15*	.22*	.18	-.16*	.74***
nhs	-.19**	-.16	-.31**	-.07	-.002
univ	.06	-.03	.12	-.05	.15*
rgn1	.08	.22	-.08	.40***	.21*
rgn2	.09	.17	-.02	.17	.27**
rgn3	.11	.17	-.02	.21**	.31***
famsz	-.05*	-.01	-.10**	-.04	.14***
city	.13*	.03	.16	.05	.11
inc	.002*	-.001	.004***	.001	-.001
pubins	.38***	.25	.59***	.21*	.69***
privins	.31***	.11	.54***	.02	.35***
emp1	.04	.25	-.20	-.17	-.39***
emp2	.08	.10	-.01	-.09	-.40***
offer	.10	-.02	.16	-.32***	.49***
h1	.57***	.10	.63***	.93***	.30**
h2	.25**	-.29*	.39**	.68***	.28**
h3	.57***	.38*	.40*	.87***	.42**
h4	-.44	-.98**	-.13	.42**	.42**
h5	.12	-.10	.10	.23**	.27***
limdy	.08***	.03***	.10***	.02**	.09***
cons	-2.34***	-2.11***	-2.48***	.69*	-1.42***

[a]The superscripts *, ** and *** denote % 10, % 5 and % 1 significance, respectively.

differentiated in order to design appropriate policy measures.

Except in the case of HOSP, throughout all the medical services, and insurance types, MH2 effect is stronger than MH1 effect. In the case of HOSP, this result drastically changes. In the case of public (resp. private) insurance, the MH1 effect leads to a %.55 (resp. % .27) change in demand, whereas MH2 leads to only a % .20 (resp. %.02) change.

The results also reveal that the overall moral hazard effect of public insurance is more severe than the overall moral hazard effect of private insurance across all the medical services. This may be due to the impossibility of screening in the case of public insurance. The difference between public insurance and private insurance is particularly remarkable in HOSP.

The results suggest an indication of MH1 even when we consider an adjustment for multiple comparisons. For example, according to the Bonferroni bounds correction, all the results related to OPER and SPMS survive. Furthermore, MH2 in both types of insurances and MH1 in public insurance in MDMS, and MH1 in HOPS also survive. The simultaneous survival of MH1 and MH2 in MDMS even though a Bonferroni bounds correction is considered builds further confidence in my basic argument that moral hazard could be separated into these two types, and hence there are qualitative differences across medical services.

The regression results (Tables 8 and 9) also reveal that some variables have positive (resp. negative) OMEs throughout all the medical services whenever they are significant, as displayed in Table 10. The first column gives the group of the variable, the

Table 10: The Overall Marginal Effects.

Class of Variables	**Always Negative**	**Always Positive**
Consumer's Attributes	SEX, WHITE, NHS	AGE, MAR, CITY
Purchasing Power	EMP1, EMP2	INC, PUBINS, PRVINS
Health Status	-	H1, H3, H5, LIMDY

Table 11: Conflicting Marginal Effects in Different Decision Stages.

Variables	**Medical Service**	**ME in Stage 1**	**ME in Stage 2**	**OME**
SEX	HOSP	-	+	-
WHITE	MDMS	+	-	-
MAR	GPMS	+	-	-
MAR	OPER	-	+	+
NHS	MDMS	+	-	-
NHS	SPMS	+	-	-
UNIV	OPER	-	+	+
OFFER	HOSP	+	-	-
H2	GPMS	+	-	-
H4	GPMS	+	-	-

second (resp. third) column lists the variables that always have a negative (resp. positive) OME on the demand. While MAR, AGE and CITY always increase the demand, SEX, WHITE or NHS always decrease the demand.

There are also variables that have conflicting (significant) effects at different decision stages. These variables and the respective medical services that their effects conflict are presented in Table 11. The first column gives the name of the variable, and the second column gives the name of the medical services for which the conflicting effect exists. The rest of the columns provide the signs of the marginal effects in Stages 1 and 2 and the sign of the OME (computed using equation (3.1)). The existence of such significant conflicting effects may provide insights in different areas. For example, the findings related to MAR in GPMS may indicate that, married people tend to decide to become a PHCC more often, but they tend to have less follow up visits.

6 Conclusion

In this paper I introduce a broader perspective on the moral hazard effect of health insurance on health care demand. This broader perspective leads to identification of qualitative differences in the moral hazard effect across medical services. I consider two demand regimes, where an individual can switch from one of to the other with a given probability. The first demand regime D_1 is the ex ante demand. In D_1, the individual has no perception to demand health care (in a given period) and the demand is always zero. The second demand regime D_2 is the ex post demand. In D_2, a need for health care is perceived. However, in D_2, the individual need not necessarily have positive demand, and zero demand is still possible due to, say, unavailability of health insurance, financial constraints and the like.

I consider the positive effect of health insurance on the probability of switching between D_1 and D_2 to be a type of moral hazard and call it MH1. The MH1 effect is analogous to the adverse effect of having health insurance on self-preventive activities. Also, MH1 is qualitatively different from the price effect of health insurance on the demand in D_2. I identify the price effect separately, and call it MH2. To analyze MH1 and MH2 effects, I parametrize both the switching probability between the two regimes and the conditional mean of the distribution of the ex post health care demand. I use the Zero-Inflated regression model that enables such a parametrization.

Using the Zero-inflated negative binomial regression model may arise concerns that the functional form I use may lead to the identification of MH1 and MH2. These concerns are largely mitigated by post-estimation analysis of a subsample that consist of those individuals that are least likely to be Potential Health Care Customers: the subsample of top % 25 indeed consists of mostly the healthy, younger and richer males.

I use a data set of 18,116 observations to analyze these decisions. The data set consists of several variables related to consumer's personal attributes, purchasing power and the health status. My findings indicate that health insurance indeed affects an individual's switching between the D_1 and D_2, in addition to the decision in D_2. In particular, the estimations indicate that both public and private insurances significantly increase the probability of switching from D_1 to D_2 in the cases of general practitioner visits and hospital stays. This is an indication of MH1. Results provide no indication of MH1 in operations and specialist visits, while the analysis of health insurance variable in D_2 indicates intense MH2 in specialist visits and operations. Some evidence of MH2 for hospital stays in the case of public insurance is also found.

My results display different patterns of moral hazard throughout different medical services when moral hazard is decomposed in this manner. This may lead to different policy implications. For example, while the moral hazard in specialist visits can be attributed to the price effect only (MH2), the moral hazard in general practitioner visits is qualitatively different: no evidence of price effect of insurance (MH2) in general practitioner visits is found, but the indication of the effect of being insured on the switching probability between the aforementioned regimes (MH1) is significant. Hence instead of high co-pays, preventive education could be a better remedy.

I also find that, throughout all the medical services considered, moral hazard is greater in the case of public insurance, especially in the case of hospital stays and operations. This difference suggests that private companies have been more successful to reduce the moral hazard effect.

Although the results indicate a variety of interesting relationships, some future work may be useful to reinforce the findings. A useful improvement is to account for the endogeneity of health insurance.

Another piece of future work is related to the development of a new class of models. The possibility of a nonlinearity in the demand for health care services due to agency problems is investigated by Pohlmeijer and Ulrich (1995). Since the first visit for a medical service is usually a person's decision but the rest is at best a collective decision of patient and the medical doctor, the nonlinearity is plausible. To incorporate this aspect of the problem, a new class of models is proposed called the Zero-Inflated-Hurdle Models, providing another interesting route for future work.

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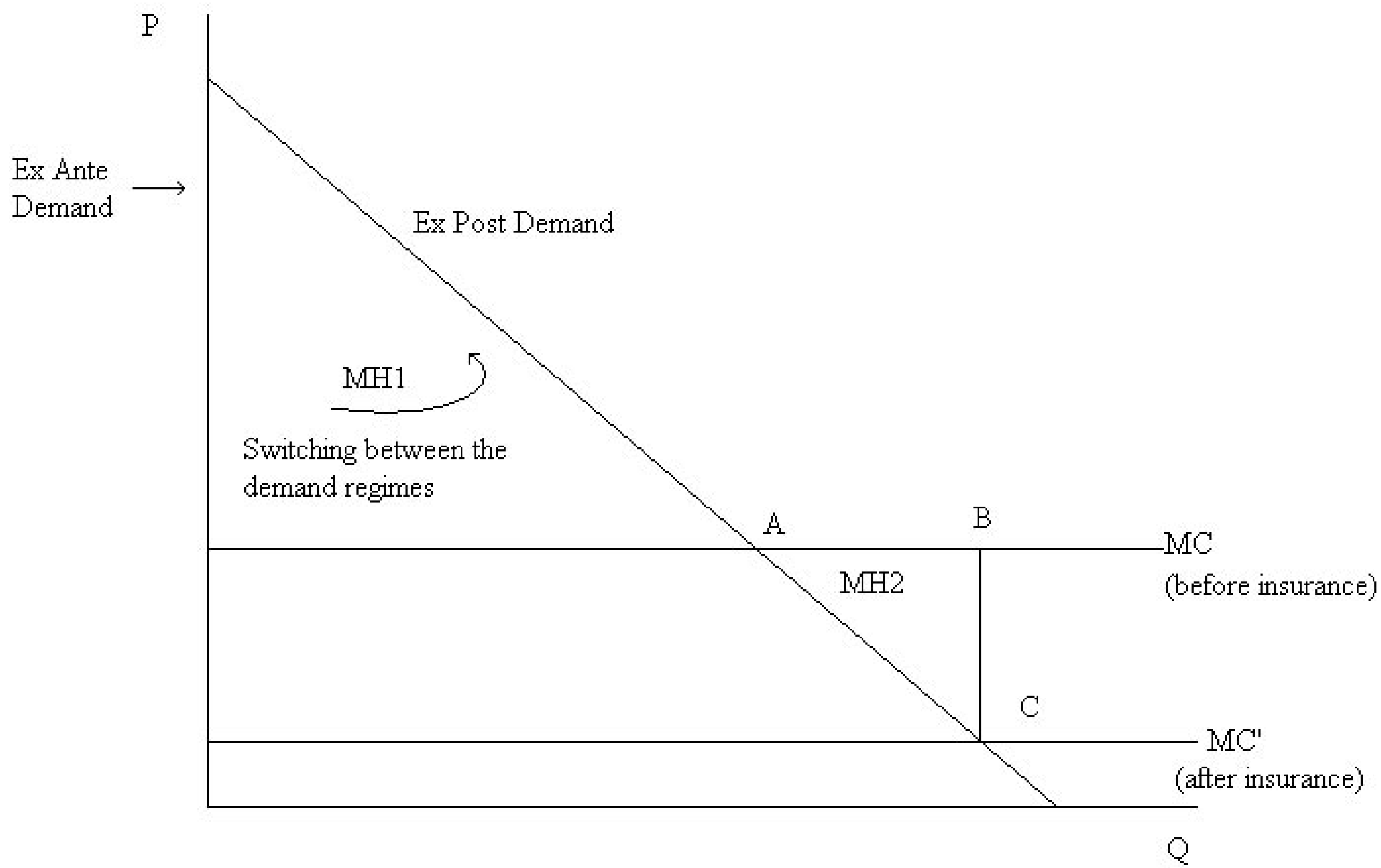

Figure 1. Two Types of Moral Hazard.

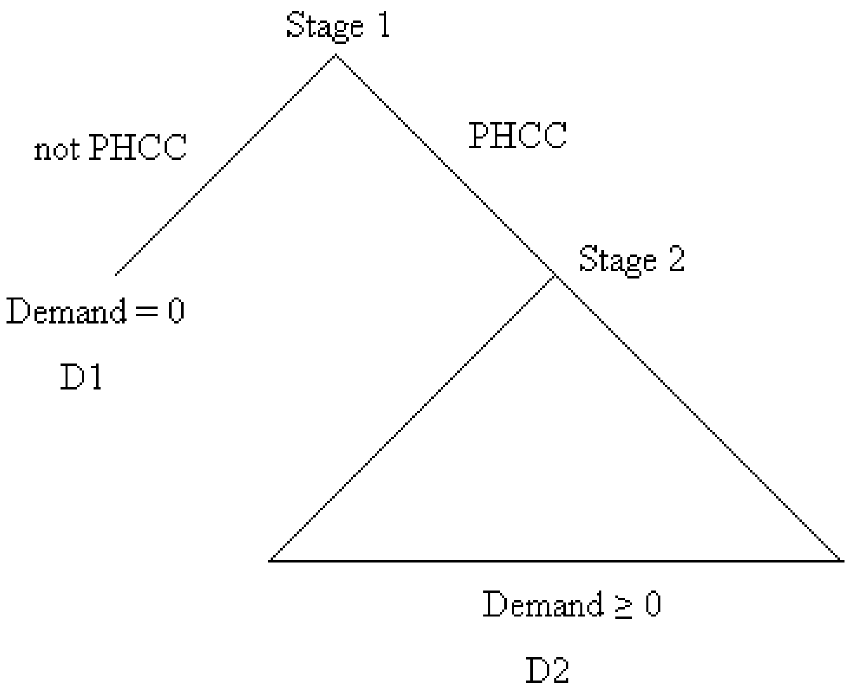

Figure 2. The decision stages and the demand regimes.

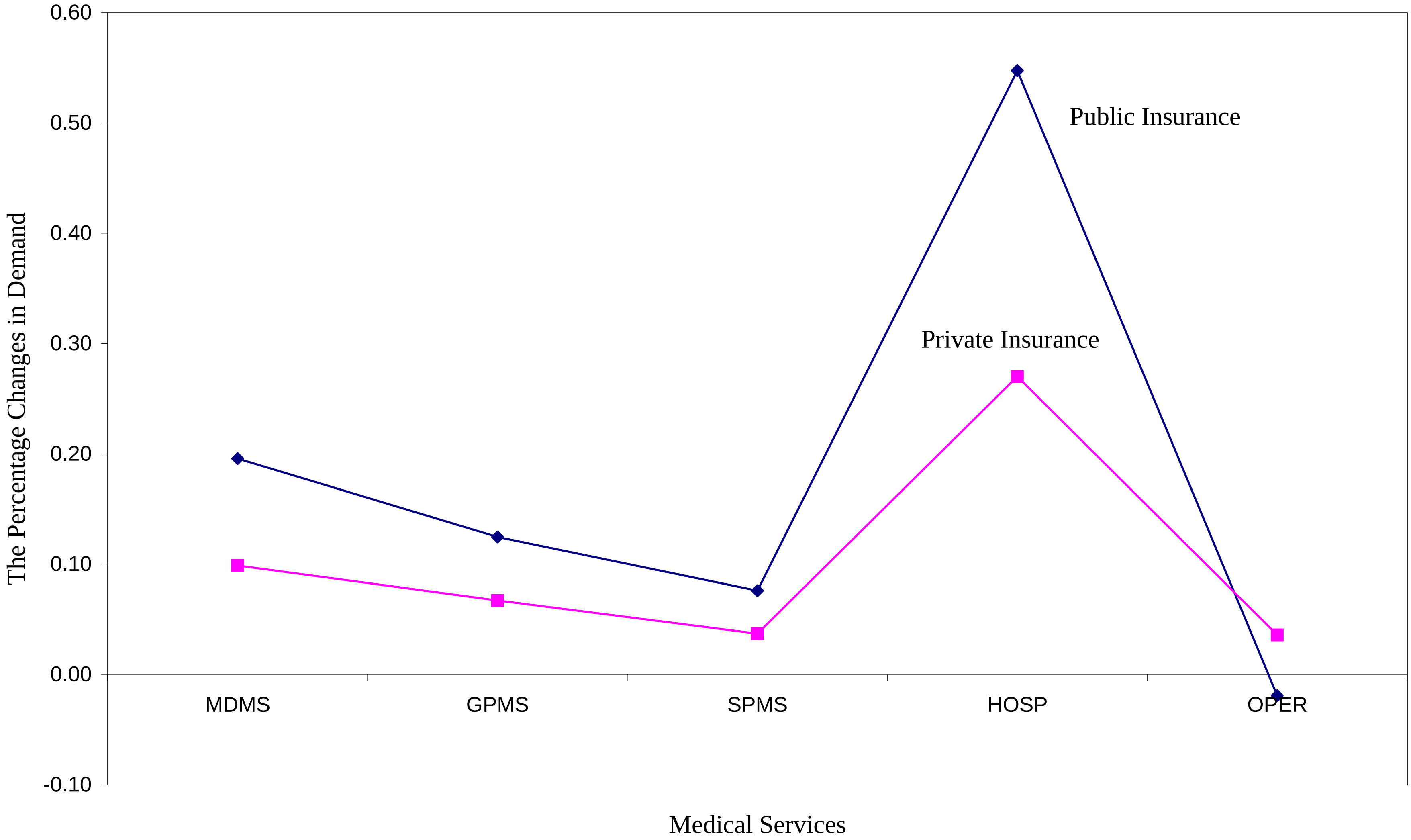

Figure 3. The Percentage Changes in Demand due to MH1 effect.

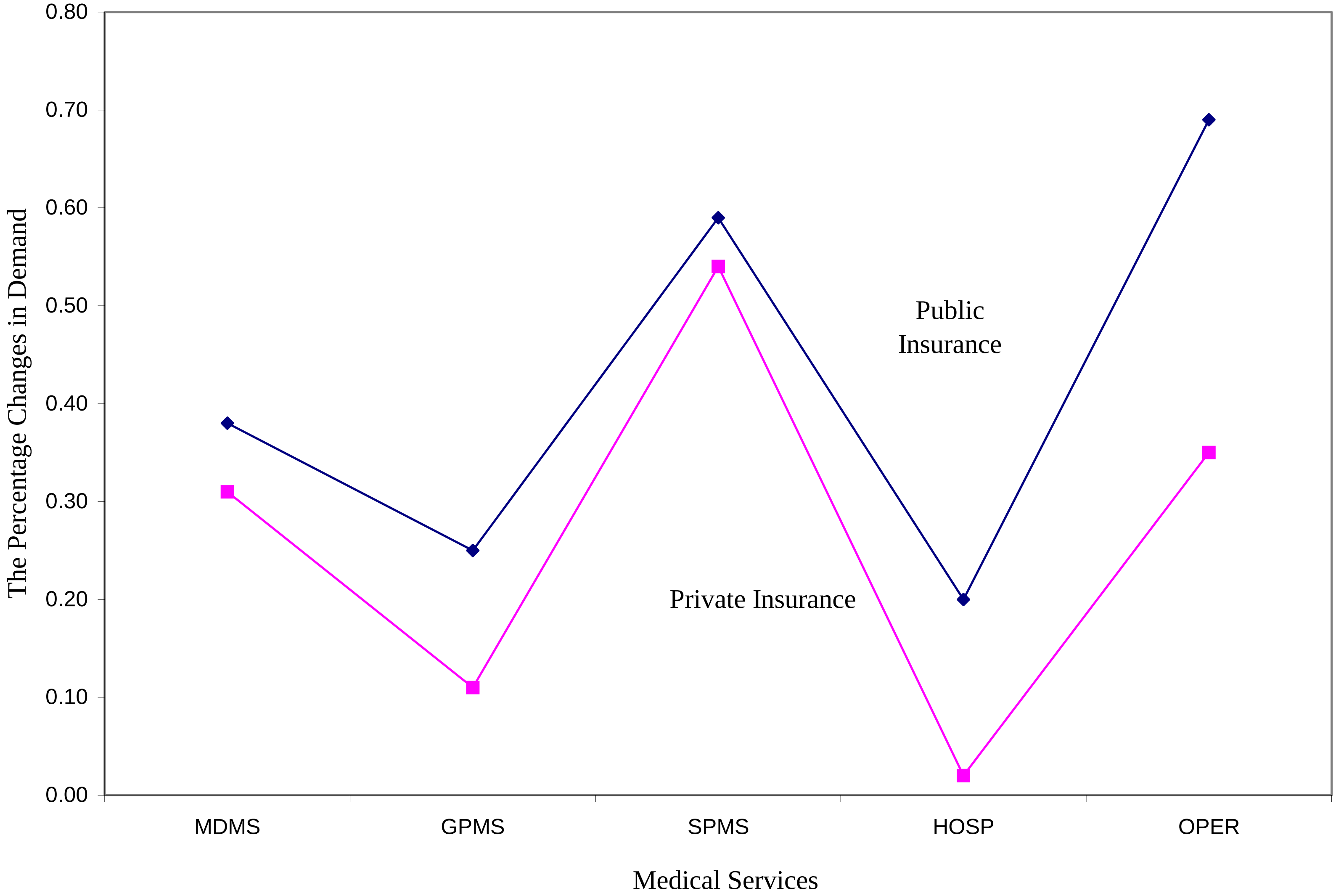

Figure 4. The Percentage Changes in Demand due to MH2 Effect.

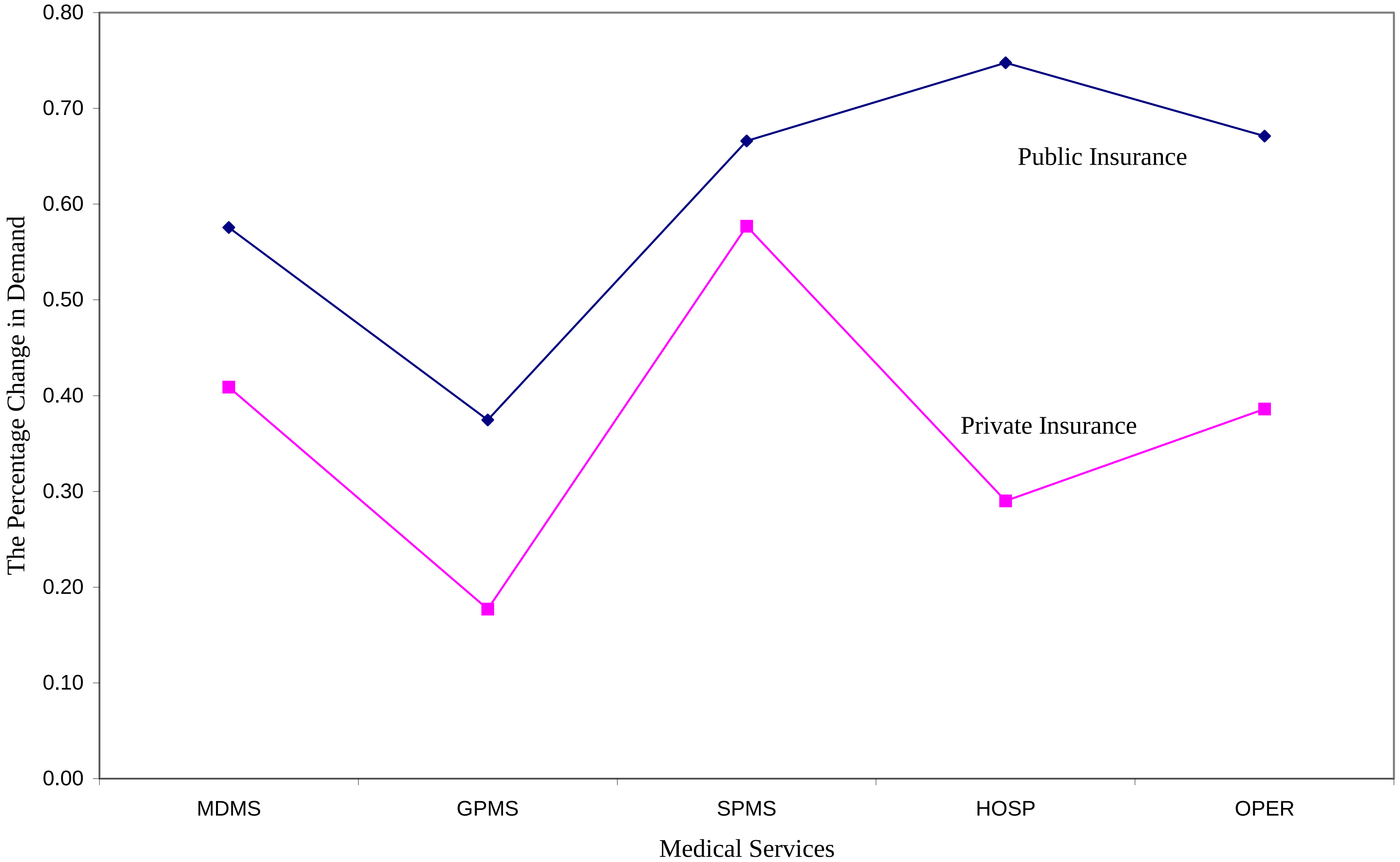

Figure 5. The Percentage Changes in Demand due to overall Moral Hazard Effect.