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Information Asymmetries and Adverse Selection in the Market for Individual Medical Expense Insurance

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ABSTRACT

This article extends the literature on adverse selection in the medical expense insurance market. Empirical tests are conducted to determine whether low risk individuals purchase less complete individual (nongroup) medical expense insurance than high risk individuals whose risk levels are unobservable by the insurer. The study also investigates whether a separating or pooling equilibrium characterizes the individual medical insurance market and whether policy cross-subsidization from low to high risks occurs. Findings are consistent with the presence of adverse selection in the individual medical expense insurance market, where low and high risks purchase a pooling insurance policy and low risks subsidize the insurance purchase of high risk insureds.

Introduction

Both theoretical and empirical studies have found that adverse selection in an insurance market reduces consumption of insurance by low risk insureds. The theoretical works of Akerlof (1970), Rothschild and Stiglitz (1976), Miyazaki (1977), and Wilson (1977) describe separating equilibria, where high risks purchase a policy with higher coverage than the policy that is purchased by low risks. Miyazaki extends the separating model to allow cross-policy subsidization, resulting in a wealth transfer from low risks to high risks. In addition to a separating equilibrium, Wilson describes a pooling model where high and low risks purchase the same policy so that low risks actually subsidize the insurance purchases of high risks.

The empirical evidence generally supports the predictions of these theoretical models. Beliveau (1981) found that adverse selection leads to reduced

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insurance consumption by low risks in the life insurance market, and Dahlby (1983) and Puelz (1990) found similar results in the automobile insurance market. Browne and Doerpinghaus (1993) found evidence of adverse selection in the market for private supplemental medical insurance for the elderly. In another study, Browne (1992a) found that low risk individuals had less complete coverage in the individual medical insurance market than in the group market, where adverse selection is believed to be less problematic. Additionally, Browne found evidence that low risks subsidize the insurance consumption of high risks in the individual medical insurance market. His results could be explained by the presence of adverse selection or by low risks receiving more coverage in the group market than they would choose if they were purchasing insurance on their own in the individual market. His study does not address whether Miyazaki's separating model or Wilson's pooling model better characterizes the individual medical insurance market.

This study extends empirical investigation of the individual medical insurance market and directly tests whether there is reduced consumption of insurance by low risks, whether a separating or pooling model best characterizes the market, and whether cross-subsidization from low to high risks occurs.

The Data, the Model and Hypotheses

The Data and Potential Tests

The data used in the study are from the National Medical Care Expenditure Survey (NMCES) conducted during 1977 and 1978.[1] Only families for which the primary insured had nongroup, individually purchased medical expense insurance and for which complete insurance policy data are available are included for analysis. The data contain extensive demographic information on those insured, including age, sex, marital status, income, and geographic location. In addition, the data contain information on any activity limitations that the insured may have as well as a measure of self-reported health status.[2]

In the study, insureds are classified as being low risk if the self-reported health status of family members is excellent, good, or fair, and they are classified as high risk if the self-reported health status of any family member is poor.[3] The health status data were collected *ex ante* in the first of the five rounds of interviews conducted during the two-year period covered by the study so that health status information does not reflect the insured's revised

[1] Data items needed for this study are not yet available from the more recent National Medical Expenditure Survey (NMES) survey conducted in 1987 and 1988.

[2] Tests indicate that there is not a multicollinearity problem between the activity limitation variable and the self-reported health status data.

[3] Tests that used alternative classifications for the risk groups (e.g., a complete series of indicator variables for health status with poor, fair, and good comprising the high risk group or poor and fair comprising the high risk group) produced no significant change in the results of the study.

expectations based on actual claims history during the covered period.[4] Using the demographic data, the activity limitation variable, and the self-reported health status variable allows for not only a test of risk-induced insurance purchase but isolation of the component of risk (self-reported health status) about which insurers are by definition asymmetrically informed.[5] Demographic and health status information from the sample are summarized in Table 1.

Table 1
Characteristics of the Group of Primary Insureds (n = 191)

	Mean	*Standard Deviation*
Age	43.1 years	14.19
Female	35.6%	0.48
Married	53.9%	0.50
White	91.1%	0.28
Family Size	2.5 persons	1.46
Education ≥ 12 years	80.6%	0.39
White Collar Employment	37.2%	0.48
Annual Income	$19,865.27	28,820.00
Live in Urban Area	40.8%	0.49
Live in Northeastern United States	15.2%	0.35
Limited Activity (across all household members)	2.1%	0.14
Self-Reported Poor Health Status (across all household members); i.e., High Risks	5.8%	0.23

Source: National Medical Care Expenditure Survey (1977-1978).

Detailed data on the policies purchased by individuals (such as policy premiums, deductible amounts, out-of-pocket maximum limits, and policy coverage limits) allow for measurement of the completeness of coverage provided by each insurance policy.[6] Data on the premiums paid and benefit amounts received are also reported (see Table 2).

The Estimation Approach

A general linear regression model is used to test whether low risk individuals purchase less complete medical coverage than high risk individuals. To

[4] Self-reported health status data may, however, reflect expectations based on pre-1977 experience.

[5] Self-reported health status is generally a good measure of serious, chronic medical conditions (see, for example, Pope, 1988).

[6] Using different measures of completeness of coverage controls for differences across insureds in how each measures and chooses completeness of coverage. These data are reported in ranges of values, and ranges with few observations have been collapsed here, producing no significant change in the empirical results.

Table 2
Insurance Policy Characteristics

	Number of Households
Deductible Amount	
$0-100	123
$101-250	25
$251-500	27
> $500	16
Out-of-Pocket Maximum	
Limited ($0-12,700)	87
Unlimited	104
Policy Limit	
$0-10,000	51
$10,001-50,000	45
$50,001-150,000	11
> $150,000	84
Premium	
Mean	$604.51
Standard Deviation	399.25
Benefits Received	
Mean	$532.14
Standard Deviation	1,840.56

test for differences in insurance purchases by high and low risks, five measures of completeness of coverage are used as dependent variables. The first three are explicit characteristics of the insuring agreement: the policy deductible, the policy out-of-pocket maximum, and the policy coverage limit. Ceteris paribus, an insurance policy provides more insurance if it has a lower deductible, if it has a lower out-of-pocket maximum, or if it has a higher coverage limit. The fourth measure uses the premium as a measure of insurance; a higher premium provides more insurance coverage, all else being equal.[7] The fifth measure of insurance is the natural logarithm of the dollar amount of indemnity benefits received from the insurance policy.[8] The assumption of lognormality better fits the benefits distribution and has precedent (see, for example, Keeler, Newhouse, and Phelps, 1977; Duan et al., 1984).[9] Finally, the model is used to test for policy cross-subsidization from low to high risks. Here the dependent

[7] Premiums are less than ideal as a measure of coverage. Insurers may be unable to discern differences in risk between insureds with inherently different risk levels, and thus, as a measure of insurance, the premium would understate the amount of insurance chosen by high risks and overstate the amount of insurance selected by low risks. The premium may also suffer as a measure of insurance if the administrative expenses of insurers differ.

[8] Unlike premiums, benefits paid reflects actual claims experience rather than the insurer's expectation of future claims. Likewise, benefits do not incorporate a loading for insurer administrative expenses as premiums do.

[9] All claims are set greater than or equal to $1 to make the logarithmic transformation feasible.

variable equals the ratio of the natural logarithm of premiums to the natural logarithm of benefits, which is a measure of price paid for each dollar of benefit received.

The hypothesis that adverse selection occurs in the individual health insurance market is not supported by the data if low risks and high risks are found to purchase policies with similar cost sharing provisions and similar premiums and derive similar indemnity benefits from the policies. If low risk individuals purchase policies with less generous cost sharing provisions and lower premiums and derive lower indemnity benefits from their insurance policies than high risk individuals, the data suggest either a Rothschild-Stiglitz or Miyazaki separating equilibrium. Evidence of cross-subsidization from low to high risks would suggest a Miyazaki equilibrium as opposed to a Rothschild-Stiglitz equilibrium. If low risks purchase medical expense insurance policies with both cost sharing provisions and premiums similar to those purchased by the high risks, and if the low risks derive fewer indemnity benefits from their coverage than the high risks, the data suggest a pooling equilibrium.

The general linear regression model used for testing across all six equations is specified as

$$Y_i^k = \underline{X_i}\,\underline{\beta} + e_i,$$

where Y_i^1 = the policy deductible amount; four ranges (0, 1, 2, 3) according to dollar amount ($0-100, $101-250, $251-500, greater than $500),

Y_i^2 = the policy out-of-pocket maximum; 1 if limited, 0 if unlimited,

Y_i^3 = the policy limit or face amount, four ranges (0, 1, 2, 3) according to dollar amount ($0-10,000, $10,001-50,000, $50,001-150,000, greater than $150,000),

Y_i^4 = the natural logarithm of the policy premium amount (in dollars),

Y_i^5 = the natural logarithm of insurance benefits received,

Y_i^6 = the ratio of the natural logarithm of premium to the natural logarithm of benefits received,

$\underline{X_i}$ = a vector of independent variables for the ith insured,

$\underline{\beta}$ = a vector of regression coefficients, and

e_i = the random error term.

The general linear model is adapted to each of the six dependent variables, that is, ordered probit (Y_i^1 and Y_i^3), probit (Y_i^2), ordinary least squares (Y_i^4), and tobit estimation (Y_i^5 and Y_i^6).

Independent Variables and Expected Signs

Table 3 describes the independent variables included in the vector $\underline{X_i}$ and three additional independent variables that are used as needed to control for differences in policy characteristics.

Age, sex, marital status, and family size are used in the individual medical expense insurance market for classification (Bluhm and Koppel, 1988).

Table 3
Definitions of Independent Variables

Age	Age in years of the primary insured
Age Sq	Age squared of the primary insured
Female	1 if the primary insured is female, 0 if male
Marital Status	1 if the primary insured is married, 0 if not married
White	1 if white, 0 if not white
Famsize 2	1 if there are 2 members in the family, 0 otherwise
Famsize 3	1 if there are 3 members in the family, 0 otherwise
Famsize 4	1 if there are 4 or more members in the family, 0 otherwise
Education	1 if the primary insured has completed 12 or more years of education, 0 if the primary insured has less than 12 years of education
W Collar	1 if the primary insured's occupation is professional, technical, administrative, managerial, or clerical; 0 otherwise
Income	Annual household income in dollars
City	1 if the primary insured resides in a standard metropolitan statistical area, 0 if not
NE Region	1 if the primary insured resides in the northeastern United States, 0 if the primary insured resides elsewhere
Ltd Activity	The minimum self-reported activity limitation across family members; 1 if any covered person reports a major limitation of physical activity, 0 otherwise
High Risk	The self-reported health status across family members; 1 if any covered family member reports poor health, 0 if excellent, good, or fair health is reported by all family members
Deduc Dummy	1 if the policy's deductible is more than $100, 0 if the deductible is less than $100
OOP Dummy	1 if the policy's out-of-pocket maximum is limited, 0 if it is unlimited
Limit Dummy	1 if the policy's coverage limit exceeds $50,000, 0 if the coverage limit is less than $50,000

Because older persons tend to use more medical services, we expect a positive relationship between age and the amount of insurance purchased. Age squared is included as a variable in the study to address the fact that the demand for medical care increases with age, but at a decreasing rate. A positive coefficient for the female variable is expected because women tend to use more medical services than men. A negative coefficient for marital status is expected if married persons substitute home health care provided by a spouse for hospital or other medical care. The sequence of family size indicator variables uses a family of one as the benchmark for comparison, and then identifies families with two, three, and four or more family members covered by the policy. Larger families are expected to purchase more insurance because their use of medical services would be greater.

The race variable (White) is included to account for possible information asymmetries which may result from restricting the insurer's use of observable information. Like certain other personal characteristics deemed socially inadmissible for rate classification purposes,[10] the use of race has been prohibited by state regulation, despite its predictive power in determining expected losses. A negative relationship between the variable White and completeness of coverage is expected due to higher mortality and moribundity rates among nonwhites, which would increase the need for medical services.

The variables Education, W Collar, and Income are included to account for differences, other than risk type, which may affect the amount of insurance purchased by the insured. We expect a positive relationship between years of education and the amount of insurance purchased, because people with more education tend to use more medical care. Similarly, the coefficients for W Collar and Income are expected to be positive.

Insurers often use geographical rating factors in pricing coverage, because claim costs are a function of local physician and hospital costs (Bluhm and Koppel, 1988). The variables City and NE Region control for medical service cost differences between rural and urban areas (costs are typically greater in urban areas) as well as by region of the country (costs are typically greater in the northeastern United States).[11]

Like age, sex, and other demographic variables used by insurers in underwriting, the variable for limited activity controls for the component of risk observable to both the insurer and insured. The limited activity variable represents information that may be observable from individual interviews or from earlier medical claim records. We expect a positive relationship between limited activity and amount of health insurance coverage purchased, because a low activity level is likely to be correlated with an increased need for medical care. However, it is unlikely that limited activity is fully observable by the insurer, because observation costs are high, relative to easily obtained demographic variables such as age and sex (especially for the insured's family members). Consequently, the relationship between limited activity and demand for insurance would not be statistically significant if relatively higher observation costs deter insurers from using activity limitation information. Furthermore, 27 states restrict underwriting on the basis of physical impairment, and insurers cannot use this information even when it is known (Browne, 1992b). Another reason for anticipating a weak relationship between limited activity and the demand for insurance may stem from varying definitions of "limited activity." Insureds with temporary disabilities (such as broken bones) and those with permanent disabilities would report activity limitations, but only those with permanent limitations would be likely to demand significantly more medical insurance.

[10] In some states, insurers are prohibited from using information on sex and marital status for rate classification purposes. However, regulatory restrictions on the use of sex and marital status for rate classification purposes were less common in 1977-1978 than they are in 1993.

[11] Preliminary tests using a full complement of indicator variables for each of the census regions yielded results similar to those obtained using only the northeastern United States indicator variable.

The health status variable allows for investigation of whether insureds with unobservably higher health risk purchase more insurance. Insureds are classified as low risks if all family members reported a perceived health status of excellent, good, or fair in the NMCES survey. If any covered family member reported poor health status, the family is considered a high risk for the purposes of this study. We expect a positive relationship between poor health and relatively more complete insurance coverage.

Table 4
Ordered Probit Regression Results
Dependent Variable: Deductible Amount

Predictor Variable	*Coefficient*	*Standard Error*	*t-statistic*
Intercept	-1.216	1.288	-0.944
Age	0.046	0.068	0.673
Age Sq	-0.54E-03	0.80E-03	-0.675
Female	0.307	0.246	1.248
Marital Status	0.359	0.313	1.146
White	-0.147	0.422	-0.349
Family Size 2	-0.122	0.329	-0.371
Family Size 3	-0.718	0.375	-1.912*
Family Size 4	0.233	0.383	0.061
Education	-0.173	0.269	-0.642
White Collar	0.118	0.216	0.546
Income	0.62E-05	0.52E-05	1.194
City	-0.164	0.216	-0.757
Northeast Region	0.108	0.255	0.425
Limited Activity	-0.241	0.793	-0.304
High Risk	-0.312	0.653	-0.479

Note: Sample size (n) = 191. Pseudo $R^2 = 0.0416$. Variables are defined in Table 3.
* Statistically significant at the 0.05 level.

Empirical Results

Our tests for completeness of insurance coverage purchased by high and low risks yielded no evidence that insureds with higher unobservable risk purchase insurance policies that entail less cost sharing. These tests include the ordered probit regression equation, where the dependent variable is based on the deductible amount (Y_i^1) (see Table 4); the probit estimation results, where the dependent variable equals 1 when an out-of-pocket maximum limit is specified in the policy and 0 otherwise (Y_i^2) (see Table 5); an ordered probit regression equation, where the dependent variable is based on the range of policy limits of the contracts purchased in the individual medical insurance market (Y_i^3) (see Table 6); and an ordinary least squares regression equation, where the dependent variable equals the natural logarithm of the premium paid for

Table 5
Probit Regression Results
Dependent Variable: Out-of-Pocket Maximum Limit

Predictor Variable	*Coefficient*	*Standard Error*	*t-statistic*
Intercept	-0.291	1.244	-0.234
Age	0.003	0.065	0.053
Age Sq	-0.21E-03	0.76E-03	-0.277
Female	-0.440	0.260	-1.692
Marital Status	-0.499	0.339	-1.470
White	0.739	0.369	2.001*
Famsize 2	0.692	0.357	1.938
Famsize 3	0.920	0.386	2.380*
Famsize 4	0.818	0.395	2.071*
Education	-0.159	0.266	-0.598
W Collar	0.340	0.221	1.539
Income	-0.71E-05	0.47E-05	-1.507
City	-0.496	0.215	-2.308*
NE Region	-0.353	0.288	-1.223
Ltd Activity	0.933	0.812	1.149
High Risk	0.548	0.481	1.138

Note: Sample size (n) = 191. Pseudo $R^2 = 0.1055$. Variables are defined in Table 3.
* Statistically significant at the 0.05 level.

Table 6
Ordered Probit Regression Results
Dependent Variable: Policy Limit

Predictor	*Standard*		
Variable	*Coefficient*	*Error*	*t-statistic*
Intercept	0.424	1.296	0.327
Age	0.027	0.064	0.423
Age Sq	-0.35E-03	0.74E-03	-0.472
Female	-0.448	0.264	-1.696
Marital Status	-1.061	0.334	-3.174**
White	0.319	0.350	0.911
Famsize 2	-0.023	0.300	-0.078
Famsize 3	0.046	0.364	0.127
Famsize 4	0.506	0.371	1.364
Education	0.181	0.233	0.778
W Collar	0.092	0.191	0.485
Income	-0.11E-05	0.35E-05	-0.310
City	0.119	0.184	0.646
NE Region	-0.566	0.276	-2.050*
Ltd Activity	0.045	0.741	0.061
High Risk	0.136	0.427	0.319

Note: Sample size (n) = 191. Pseudo $R^2 = 0.0732$. Variables are defined in Table 3.
* Statistically significant at the 0.05 level.
** Statistically significant at the 0.01 level.

Table 7
Ordinary Least Squares Regression Results
Dependent Variable: Natural Logarithm of the Premium Paid (Ln$)

Predictor Variable	*Coefficient*	*Standard Error*	*t-statistic*
Intercept	284.508	335.142	0.849
Age	-3.822	17.302	-0.221
Age Sq	0.096	0.204	0.470
Female	35.121	68.673	0.511
Marital Status	92.870	89.896	1.033
White	49.614	97.793	0.507
Famsize 2	88.770	92.150	0.963
Famsize 3	265.803	100.988	2.632**
Famsize 4	359.405	103.166	3.484**
Education	-31.962	70.929	-0.451
W Collar	26.642	58.587	0.455
Income	0.27E-02	0.12E-02	2.336**
City	-10.199	58.547	-0.174
NE Region	8.937	76.319	0.117
Ltd Activity	231.114	214.575	1.077
High Risk	-100.230	132.588	-0.756
Deduc Dummy	-110.784	56.072	-1.976*
OOP Dummy	-3.604	57.058	-0.063
Limit Dummy	57.006	57.872	0.985

Note: Sample size (n) = 190. R^2 = 0.2995. Variables are defined in Table 3.
* Statistically significant at the 0.05 level.
** Statistically significant at the 0.01 level.

medical expense insurance (Y_i^4) (see Table 7).[12] The findings support a pooling, rather than a separating, equilibrium model.

In the tobit regression equation, where the dependent variable equals the natural logarithm of medical benefits paid by the insurance policy (Y_i^5), we find a statistically significant positive relationship between benefits and the poor health variable (see Table 8). This provides evidence that insureds with greater unobservable risk receive more benefits than lower risk insureds.

Table 9 reports the results of estimation of the tobit equation which tests for cross-subsidization from low to high risks (Y_i^6). The coefficient estimate for High Risk is negative and statistically significant, suggesting that insureds

[12] The relatively low values for the pseudo R^2 and R^2 statistics are due to the structure of the limited dependent variable models, which dictates that pseudo R^2 values are inherently low (see Maddala, 1983). Across all equations however, the low pseudo R^2 and R^2 values are consistent with insurers' classifying risks only to the point that it is economically efficient to do so (see Harrington and Doerpinghaus, 1993). That is, insurers do not find it profitable to incur greater observation costs in order to further refine risk classes of insureds, and thus the model used for predicting premiums and insurance purchase by high and low risks has relatively low explanatory power.

Table 8
Tobit Regression Results
Dependent Variable: Natural Logarithm of Medical Benefits (Ln$)

Predictor Variable	*Coefficient*	*Standard Error*	*t-statistic*
Intercept	-6.888	4.961	-1.348
Age	0.022	0.246	0.090
Age Sq	0.53E-03	0.28E-02	0.183
Female	1.279	0.992	1.290
Marital Status	0.142	1.238	0.115
White	1.846	1.475	1.251
Famsize 2	2.572	1.272	2.022*
Famsize 3	4.183	1.395	2.999**
Famsize 4	4.347	1.412	3.078**
Education	0.306	0.995	0.308
W Collar	0.090	0.824	0.109
Income	-0.59E-06	0.16E-04	-0.037
City	-0.472	0.817	-0.577
NE Region	2.169	1.027	2.112*
Ltd Activity	1.075	2.739	0.393
High Risk	4.237	1.715	2.470**
Deduc Dummy	-0.764	0.801	-0.954
OOP Dummy	-1.659	0.815	-2.035*
Limit Dummy	2.369	0.837	2.829**

Note: Sample size (n) = 190. Pseudo R^2 = 0.1422. Variables are defined in Table 3.
* Statistically significant at the 0.05 level.
** Statistically significant at the 0.01 level.

with higher unobservable risk receive more indemnity benefits per dollar of premium than do lower risks. The evidence is consistent with cross-subsidization from low risk to high risk insureds.

Conclusions

Empirical evidence from the individual medical insurance market shows that insureds with higher unobservable risk do not purchase insurance policies with significantly different cost sharing provisions than low risk insureds. However, high risks receive more indemnity benefits per premium dollar than low risks. These findings are consistent with the presence of adverse selection in the individual medical expense market where high and low risks purchase a pooling policy that implicitly subsidizes those with unobservably poor health. Thus, if the demand for insurance is not inelastic, the empirical evidence is consistent with the theory that low risk insureds consume less insurance than they would in a market free of adverse selection.

Table 9
Tobit Regression Results
Dependent Variable: Ratio of Premiums (Ln \$)/Benefits (Ln \$)

Predictor Variable	*Coefficient*	*Standard Error*	*t-statistic*
Intercept	5.571	2.652	2.101
Age	0.035	0.137	0.255
Age Sq	-0.69E-03	0.16E-02	-0.427
Female	-0.478	0.543	-0.881
Marital Status	0.180	0.716	0.251
White	-0.691	0.768	-0.900
Famsize 2	-1.003	0.736	-1.363
Famsize 3	-1.631	0.808	-2.017*
Famsize 4	-1.782	0.825	-2.160*
Education	-0.292	0.565	-0.517
W Collar	0.125	0.463	0.269
Income	0.18E-05	0.92E-05	0.197
City	0.161	0.465	0.348
NE Region	-1.422	0.615	-2.313*
Ltd Activity	-1.359	1.846	-0.736
High Risk	-2.809	1.097	-2.559**
Deduc Dummy	0.186	0.445	0.418
OOP Dummy	0.799	0.452	1.767
Limit Dummy	-0.929	0.457	-2.033*

Note: Sample size (n) = 190. Pseudo R^2 = 0.0474. Variables are defined in Table 3.
* Statistically significant at the 0.05 level.
** Statistically significant at the 0.01 level.

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