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Abstract

Using data from the 1998 Wave of the Health and Retirement Study, we examine the effect of social interactions on the health insurance choices of the elderly. We find that having more social interactions, as measured by contacts with friends and neighbors, reduces the likelihood of enrolling in a Medicare managed care plan relative to purchasing a medigap policy or having coverage through Medicare alone. Our estimates indicate that social networks are an important determinant of the health insurance choices of the elderly and provide suggestive evidence that "word-of-mouth" information sharing may have played a role in the preference of some seniors for traditional indemnity insurance over managed care.

1. Introduction

The ability of consumers to discern quality differences between health plans[1] is a necessary ingredient for the efficient operation of health insurance markets generally and is likely to be especially important in the non-group market where individuals cannot rely on employers to serve as intermediaries between themselves and their insurer. Policymakers have been particularly concerned about the informational demands placed on the elderly by the numerous and often complex health insurance options existing for retirees. Initially, these concerns were focused on the difficulty that many seniors experienced in choosing among the large number of medigap policies that were once available; indeed, it was this concern in part that led to the mandated consolidation of medigap into ten standardized benefit designs. However, despite this reform, one could argue that the informational burden on the elderly remains large due to the availability of private managed care plans as an additional option for Medicare beneficiaries. In contrast to a pure fee-for-service arrangement, the choice of a managed care plan often implies the choice of a specific provider, hospital, and style of care. Because many of the most important characteristics of both a plan and its providers are not easily observable, seniors must find some source of information on which to base their decisions.

Exactly what information seniors have, and how it bears on their insurance choices, has been the subject of several recent studies. For the most part, these studies have focused on what might be called "formal information," i.e., plan rankings or other constructed measures of plan performance. Examples include the Health Plan Employer Data and Information Set (HEDIS) and the Consumer Assessment of Health Plans Study (CAHPS), both of which are available to Medicare beneficiaries through a website maintained by the Centers for Medicare and Medicaid Services (see Uhrig and Short (2002/2003) for details). Such studies have found mixed results in assessing the impact of formal information on the plan choices of the elderly. For example, Uhrig and Short (2002/2003) found that HEDIS- and CAHPS-derived quality information distributed during a laboratory experiment did not have a significant impact on the choice between remaining in traditional Medicare and enrolling in a Medicare HMO, although the information did affect the choice between HMOs for those who selected HMO coverage.

The mixed evidence on the value of formal information suggests that much of the information that elderly consumers find useful when selecting a health plan may not be available in the kinds of ratings used in the current generation of HEDIS and CAHPS measures[2], or, alternatively, that official ratings simply do not carry the same weight as information conveyed by friends or neighbors. This, of course, raises the question of what information seniors do use, and what impact, if any, such information has on their choices.

Several recent studies provide evidence that informal "word-of-mouth" information sharing, also known as social learning, is an important determinant of financial decisions in other contexts, leading us to conjecture that a similar phenomenon may play a role in the health insurance choices of retirees. For example, Hong, Kubik, and Stein (2004) document the influence of social learning on the decision to invest in the stock market, while Duflo and Saez (2002) and Sorensen (2002) examine its impact on the choice of employer-sponsored retirement and health insurance plans, respectively.

Most previous work on social learning has used data on the choices made by coworkers to test for the presence of peer effects among employed adults (Duflo and Saez, 2002; Sorensen, 2002). This approach is not possible in the current context because there is no data set of which we are aware that provides information on peer behavior for retirees, nor is there any way to directly observe information flows across individuals. Instead, we follow the approach adopted by Hong, Kubik and Stein (2004) in their study of stock market participation in which households are categorized in terms of their social interactions with friends and neighbors and participation rates among "social" and "non-social" households are compared.

A potential weakness of using sociability to proxy for information exchanged through social networks is that such a measure may be correlated with personality traits that independently influence insurance choices. For example, it might be that more sociable households are more risk tolerant or more optimistic than less sociable households, thus making these households more open to purchasing newer or "riskier" insurance products, such as Medicare HMOs. We attempt to address this problem in two ways. First, we include proxies for a variety of household attitudes as control variables in our regressions. Second, because our control variables may not capture all attitudinal differences that are potentially correlated with sociability and plan choice, we also test some subsidiary implications of the information sharing interpretation of our sociability variable. The first is that better educated households may find it easier to obtain the necessary information on their own (by reading articles in newspapers or magazines, for example), while less educated households may be more limited in their ability to process such information and, as a result, may be more likely to solicit opinions from friends and neighbors. The second relates to the fact that if sociability does capture information sharing as we hypothesize, then it should only have an impact on purchases of complex or unfamiliar products. We test this proposition by examining the effect of sociability on the propensity of households to hold life insurance and maintain a checking account.

We find that greater social interaction, as proxied by interactions with friends and neighbors, reduces the likelihood of enrolling in Medicare managed care plans by about 4 percent. Given a baseline managed care enrollment probability of 13.2 percent, this translates into a 30 percent relative reduction in the likelihood of an elderly household being enrolled in a Medicare HMO. Consistent with an information-sharing interpretation of the results, we find that the influence of sociability on Medicare HMO enrollment exists primarily for less educated people who may have a greater need to rely on others for information. We also find that while sociability affects the decision to enroll in a managed care plan, it does not exert a significant influence on the decision to hold life insurance or maintain a checking account.

Our results indicate that social networks are an important determinant of the health insurance choices of the elderly and provide suggestive evidence that word-of-mouth information sharing may have played a role in the preference of some seniors for fee-for-service insurance over managed care. Our findings also reinforce the conjectures offered in several earlier studies that formal sources of information may have been less effective than originally hoped because they fail to capture the kind of "soft" information exchanged in informal settings[3], or because people are more apt to believe reports from friends and neighbors.

The paper proceeds as follows. In Section 2.1, we briefly review the insurance options available to retirees. In Section 2.2, we discuss our data. In Section 2.3, we present our main results and discuss several specification checks. In Section 2.4, we provide some additional justification for an information-sharing interpretation of our results by examining how the influence of sociability varies with education and product familiarity / complexity. Concluding remarks are offered in Section 3.

2. The Health Insurance Choices of the Elderly

2.1. Background

Americans aged 65 and over have three primary health insurance options to choose from.[4] First, they can obtain coverage exclusively through Medicare, a federal program that provides coverage for most medical expenses, aside from prescription drugs, provided that the enrollee receives both part A (hospital coverage) and part B (physician coverage). Second, because the Medicare program subjects beneficiaries to deductibles and co-payments, and imposes some coverage exclusions, most seniors have chosen to supplement their Medicare coverage with a private insurance policy, known as a Medicare supplement or medigap policy, that partially insures them against the gaps in their Medicare coverage. Beginning in the mid-1980s, a third option was added, which allows Medicare beneficiaries to enroll in a private managed care plan in lieu of obtaining coverage through the Medicare program. Medicare managed care plans typically provide more generous coverage than traditional Medicare, for example by providing more “first dollar” coverage and/or by providing partial coverage for prescription drugs, but at the expense of exposing seniors to the strictures of managed care, such as restricted choice of physicians and hospitals. In what follows, we analyze how sociability influences the propensity of retirees to choose the third option (Medicare managed care), relative to the more traditional alternatives of stand-alone Medicare or Medicare supplemented with medigap.

2.2. Data

Our data are taken from the 1998 Wave of the Health and Retirement Study (HRS), a longitudinal survey providing information on the demographic characteristics, health insurance coverage, and public program participation of the elderly and near-elderly beginning in 1992, with follow-up surveys conducted every two years. The original sample is nationally representative of the cohort born in 1931-1941. Beginning with Wave 4 in 1998, the HRS also added three new cohorts to the survey. The first group was composed of people already being followed in a companion survey to the HRS, known as the Study of Assets and Health Among the Oldest Old (AHEAD). The AHEAD cohort consists of households with a member born in 1923 or earlier. The second group added were households with a member born during the period 1924-1930, and dubbed the “Children of the Depression” cohort. The final addition was a group of individuals born between 1942 and 1947, known as the “War Baby” cohort.

We use a single wave of the HRS in our analysis because a panel model with fixed effects would be based on within-household changes in sociability and insurance purchases between 1992 and 1998. Because sociability exhibits little variation over time, this type of identification strategy was not possible. We focus on the 1998 wave, rather than the earlier waves, to maximize the number of respondents with Medicare coverage (due to the addition of the AHEAD, "Children of the Depression," and "War Baby" cohorts).

The unit of observation for our analysis is the household. This is because several variables of interest, most notably our sociability measure, are only asked of one member of the household. Our sample consists of all households in the 1998 HRS with a member who is a Medicare beneficiary aged 65 or older. The HRS provides fairly extensive information on survey respondents, including information on their demographic characteristics, income, wealth, employment status, health status, insurance holdings, and utilization of medical care. Some questions are asked of one household member and are designed to apply to the household as a whole while others are asked of each household member separately. For the latter questions, we create a household measure by classifying the household based on the individual response that would most distinguish it from the "typical" household in the data. For example, in the case of ethnicity, we categorize a household as being Hispanic if either member of the household reports being Hispanic. Similarly, for age and education we place the household in the category associated with the highest age and education level reported by household members. For health status and medical utilization, households are classified based on the lowest health status and highest utilization of either member.

Insurance holdings are likewise categorized, with households being classified as enrolled in a Medicare managed care plan (HMO) if either member of the household is. If neither member is enrolled in a Medicare HMO, then the household is classified as having a medigap policy if either member holds a medigap policy. If neither member holds a medigap policy, then the household is classified as having "stand alone" Medicare coverage. In our estimation sample, only 6 percent of households rely exclusively on Medicare; approximately 81 percent hold a medigap policy while 13 percent are enrolled in a Medicare HMO.[5] Given that 94 percent of households modify their Medicare coverage in some way, the primary variation in the data relates to the manner in which Medicare coverage is augmented.

The sociability measure we use is derived from two HRS questions. The first asks respondents whether they have good friends in the neighborhood. The second asks respondents how many times they get together with neighbors just to chat or for a social visit. Responses to the second question exhibit large mass points at zero visits (approximately 20 percent of households) and at one visit (approximately 60 percent of households), indicating that there are essentially three margins of sociability embedded in this question: no visits, one visit, and more than one visit. In experimenting with the possible cut-offs, we found the relevant margin to be no interactions with neighbors vs. some interactions (one or more). Thus, a household is defined as being "sociable" if the respondent indicates the presence of friends in the neighborhood or indicates that they get together socially with their neighbors at least once a year. Approximately 89 percent of households are classified as "sociable" using our criteria; thus, we are comparing households with any level of social interaction to those with none. This seems appropriate when thinking about the amount of interaction required to obtain information on health plans and is in keeping with the threshold used by Hong, Kubik and Stein (2004) in their study of social interactions and stock market participation.[6]

As discussed in the Introduction, a potential weakness of using sociability to proxy for information sharing is that such a measure may be correlated with unobserved personality traits that independently influence insurance choices. One way that we attempt to address this problem is by including proxies for household attitudes as control variables in our regressions.[7] These are listed collectively as "mental status" dummies in most of our results, but are described separately in the summary statistics listed in Table 1. The eight mental status dummies are: "felt depressed"; "felt everything was an effort"; "sleep was restless"; "felt happy"; "felt lonely"; "felt sad"; "could not get going"; and "had a lot of energy." We expect that, as a group, these variables should be correlated with personality traits that might be important for health insurance choices, such as optimism or a willingness to try new things.

We also rerun our baseline specifications adding controls for risk tolerance from Wave 1 of the HRS merged with the Wave 4 data that we use for our analysis. Because the risk tolerance measures are only available for the original HRS cohort (the 1931-1941 birth cohort), our sample sizes are significantly reduced due to the loss of the AHEAD, “Children of the Depression,” and “War Baby” cohorts. The risk tolerance variables are constructed based on hypothetical questions designed by Barsky et al. (1997) for the purpose of measuring attitudes toward risk.[8] Based on their answers to these questions, households can be partitioned into four groups defined by two indicator variables. Because of the small sample sizes involved, we present these results only as a sensitivity check.

Table 1 provides descriptive statistics for our sample.[9] Approximately 90 percent of the households in our sample are classified as white, 67 percent are married, and about 7 percent have at least one member who is employed in some capacity. Average household income is roughly $14,000 and average household wealth is $173,000. The HRS households score well on functional status (ability to walk several blocks, climb stairs, or bend over to pick up a dime), but many households have at least one member who has, or has had, a chronic medical condition (24 percent of households have a member who has had cancer, 37 percent have a member with a heart condition, and 18 percent have a member who suffers from depression). In terms of utilization, 46 percent of households have a member with an overnight hospital stay during the past two years, 15 percent have received home health care during that time, and 3 percent have experienced a nursing home stay.

2.3. Social Learning and Medicare HMO Enrollment

We estimate a probit model with a dependent variable taking the value “one” if a household has at least one member enrolled in a Medicare HMO, and “zero” otherwise.[10] The marginal effects reported in Table 2 indicate how a one-unit change in each explanatory variable affects the probability of enrolling in a Medicare HMO relative to retaining traditional Medicare coverage and either purchasing a medigap supplement or relying on Medicare alone.[11] Column (1) contains controls for basic demographics. Column (2) adds indicator variables for income and wealth deciles and employment status (7 categories). Column (3) adds three measures of functional status, 11 chronic condition indicators, 8 mental status indicators, and an indicator for whether the household is satisfied with their health care. In column (4), we add several utilization variables. State dummies are included in all specifications.

As shown in Table 2, the effect of sociability on Medicare HMO enrollment is quite robust across all four specifications and is always statistically significant at the 0.01 level or better. Sociable households are about 4 percent less likely to have a member enrolled in a Medicare HMO. Given a baseline enrollment probability of 13.2 percent, this translates into a 30 percent relative reduction in the likelihood of an elderly household having a member with coverage from a managed care plan, a finding which suggests that better informed retirees are significantly less likely to opt for the managed care alternative.

Before turning to our specification checks, a couple of other results are worth noting. Focusing on column (4) of Table 2, we find that black households are significantly more likely to have coverage from a Medicare HMO than white households, while those who are separated, widowed, or never married are significantly less likely to enroll in an HMO than those who are married. The interpretation of the utilization variables is complicated by their endogeneity with respect to the chosen insurance coverage. That said, we find a significant negative association between the number of overnight hospital stays and the likelihood of being enrolled in an HMO. It is not possible to ascertain whether this reflects favorable risk selection or the tighter utilization controls imposed by managed care organizations. In the same vein, we find that having used home health care in the past two years is positively correlated with Medicare HMO enrollment.

Other variables that exert a significant influence on HMO enrollment, but which are not reported in Table 2, are: age (relative to the omitted category, 65-69 year olds, increasing age monotonically reduces the probability of HMO coverage up until age 84, after which the effect remains negative for 85-89 year olds, but becomes insignificant thereafter); employment status (relative to those who are current working, those who are unemployed and looking for work are significantly more likely to have HMO coverage, whereas those who are disabled, retired, or classified as homemakers are significantly less likely to have coverage from an HMO); and the presence of certain chronic medical conditions (those suffering from cataracts and depression are less likely to join an HMO, while those with diabetes are more likely). Looking across the income and wealth deciles, we generally find that both are negatively related to Medicare HMO enrollment, but few of the individual coefficients are statistically significant, perhaps because of the high degree of collinearity with other variables.

We also found that those who reported having "a lot of energy" were significantly more likely to have coverage from an HMO, a finding which, when coupled with the negative influence of depression on HMO enrollment, suggests that our "mental status" variables are picking up some of the attitudinal differences that we hoped to control for. However, the variables that are potentially the most important in this regard are those that measure the household's tolerance for risk. As discussed previously, we have created two indicator variables for risk tolerance using the questions devised by Barsky et al. (1997). Unfortunately, these questions were only asked of those in the first wave of the HRS, which dramatically reduces the size of the available sample, owing to the loss of the AHEAD, "War Baby," and "Children of the Depression" cohorts that were added subsequent to Wave 1. As a consequence, we do not include these variables in our primary regressions presented in Table 2, but instead include them as a sensitivity check in Table 1A. Columns (1)–(4) of Table 1A replicate the four specifications estimated in Table 2 using the Wave 1 sample. In columns (5)–(8), we estimate identical specifications that differ only by the incorporation of our two risk tolerance indicators. Comparing columns (1)–(4) to columns (5)–(8) reveals that our results are virtually identical, both in terms of magnitudes and statistical significance, when the risk tolerance variables are added. This provides some evidence that our benchmark estimates from Table 2 are unlikely to be biased by differences across households in attitudes toward risk.

As an additional robustness check, we also estimated a multinomial logit model that breaks out the "Medicare only" and "Medicare plus medigap" households into separate categories. Results for this model, which are qualitatively similar to those from the probit specification, are displayed in Table 2A of the Appendix. In contrast to the results for Medicare HMOs, where our sociability variable is statistically significant in every specification considered, sociability never exerts a statistically significant influence on the decision to purchase a medigap policy (relative to relying on Medicare alone). We view this finding as being consistent with an information sharing interpretation because, a priori, one would expect that more information would be required to enroll in a managed care plan than to choose an indemnity policy from among a small set of standardized insurance products.

2.4. Additional Evidence

In this section, we provide some additional evidence that our sociability measure is likely capturing information exchanged through social networks. We do so by testing two subsidiary implications of the information-sharing hypothesis. The first is based on the premise that social learning and other types of learning are substitutes in the sense that gaining knowledge from one source lessens the need to acquire information from another source. In the current context, this amounts to assuming that information obtained from newspapers, magazine articles, or the internet reduces the marginal gain from seeking information from friends and neighbors. To the extent that more educated people are better able to process such information, we would expect that conversations with friends and neighbors would have less of an impact on their insurance choices.

We test for such an effect by re-estimating the probit models from Table 2 allowing the effect of sociability to vary across households with different levels of education. Results are presented in Table 3, where an indicator for having at least one member of the household with a college education is interacted with our sociability variable. Under this formulation, the effect of sociability on Medicare HMO enrollment among less educated households is given by the coefficient on the sociability variable while the effect for better educated households is given by the sum of the coefficients on the sociability variable and its interaction with the college indicator. Consistent with the above hypothesis, we find that sociability has a large and statistically significant effect for households without a college graduate, but essentially no effect for college educated households.

A second implication of the information sharing hypothesis is that sociability should *not* affect the decision to purchase products about which households are already well informed, or that are relatively simple to use. In Table 4, we focus on life insurance and checking accounts, two financial products which, due to their familiarity and simplicity, should not be affected by social interactions with friends and neighbors. We consider life insurance as an additional check on the possibility that sociability could be correlated with risk aversion, notwithstanding the sensitivity check using the risk tolerance measures described earlier. Our examination of checking account usage is motivated by two possible confounders. The first is a concern that more sociable households might be more trusting, and therefore more willing to expose themselves to the restrictions associated with managed care. An admittedly weak test of this conjecture, but the best one available to us, is to investigate whether sociability predicts checking account use. Among the elderly, particularly the portion of our sample composed of the

"Children of the Depression" cohort, there may be a distrust of financial institutions that leads some households to avoid placing money in checking accounts. While households without checking accounts represent a relatively small portion of our sample (approximately 7.5 percent), it is not implausible that there could be correlation between this group and those that eschew social interactions. A second rationale for looking at checking account usage is that elderly households that do not have friends or interact with neighbors could be less financially sophisticated in general than more sociable households, and therefore less apt to venture beyond traditional Medicare coverage. This seems unlikely given that we found no effect of sociability on the propensity to purchase a medigap policy in our multinomial logit model, but testing for an effect of sociability on checking account usage provides an additional piece of evidence on this score.

Table 4 replicates the probit models estimated in Table 2, using as dependent variables indicators for whether a household owns a life insurance policy (approximately 82 percent of households) or maintains a checking account (92.5 percent of households). The results from these specification checks are consistent with an information sharing interpretation of our sociability variable; in no case does sociability exert a significant influence on the propensity to hold either product, and the marginal effects are below one percent in all but one specification.

3. Conclusions

In this paper, we have examined the effect of social learning on the health insurance decisions of the elderly by linking the observed choices of retirees to measures of their social interactions with others. Our results suggest that social networks may play a role in disseminating health insurance information among the elderly, a finding consistent with several recent surveys of retirees. Specifically, we find that more sociable households, defined as those who have friends nearby or who interact with their neighbors, are 4 percent less likely to enroll in a Medicare managed care plan. Given that only 13.2 percent of households in our sample have coverage from a Medicare HMO, this translates into a 30 percent relative reduction in the likelihood that an elderly household selects coverage from a managed care organization.

Our findings suggest that informal exchanges of information among the elderly may have played a role in the preference of some retirees for traditional indemnity insurance over managed care. They also provide indirect evidence that is consistent with the conjectures of several researchers that formal sources of information (such as HEDIS- and CAHPS-derived plan rankings) may have been less effective than once hoped because they are unable to capture the kind of "soft" information exchanged in informal settings, or because consumers are simply more likely to believe reports from those they know personally. More tentatively, our results raise the possibility that there could be multiplier effects associated with the distribution of quality information to retirees. Thus, if official sources of information were to improve to the point where they were widely used and trusted by the elderly, our findings suggest that it may be efficient to "piggyback" on their social networks by distributing information to only a subset of beneficiaries (e.g., to a randomly-selected subset of the retirees living within a given Census tract or block).

One limitation of our study is that we are not able to directly measure peer effects, as done by Duflo and Saez (2002) and Sorensen (2002). To do so, we would need information on both the plan choices of retirees and either their geographic or social proximity; information that is not currently available for this group.[12] Instead, we have opted for the more "reduced form" approach taken by Hong, Kubik and Stein (2004), in which observed choices are compared across households having different degrees of social interaction. While we believe that the evidence generated here strongly suggests an important informational role for social networks among the elderly, additional progress on this subject will likely require the use of data that is sufficiently detailed to permit the magnitude of peer effects to be estimated.

Endnotes

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1. The information problem considered in this paper is related to the unobservability of certain attributes of health insurance plans and the ability of consumers to acquire this information from others. This is distinct from the problem, confronted by insurers, of determining an individual's risk type in the presence of asymmetric information (see, for example, Crocker and Snow, 1985 and 1986).

2. Moreover, as noted by Short et al. (2002), the quality information provided by the Centers for Medicare and Medicaid Services is not as finely targeted as most private-sector report cards on the specific options existing within a given geographic area.

3. In two of the first papers to analyze the relationship between health plan report cards and observed plan choices (Chernew and Scanlon, 1998; Scanlon and Chernew, 1999), the authors conjecture that the absence of a consistent relationship between plan rankings and enrollments in a large employer group was likely due, in part, to friends and colleagues having provided a more comprehensive assessment of the plans than was possible using the early HEDIS measures.

4. There are other, less common sources of insured medical care for the elderly, such as the CHAMPVA program for veterans. Because of the small numbers of observations, we omit these from our analysis.

5. Note that our sample is not representative of Medicare beneficiaries generally for two reasons. First, the HRS does not provide a sample of all Medicare beneficiaries, only those who are in the age cohorts followed by the survey. Second, because our sociability measure varies only at the household level, our numbers apply to households rather than individuals.

6. Hong, Kubik and Stein (2004) note that, "A large body of work in sociology supports the premise of using these sorts of variables as measures of the extent to which households have informative interactions with one another." The notion that even casual interactions among friends and neighbors can lead to substantial flows of information is documented by Granovetter (1983) in a survey of research on information exchanged through social networks, a phenomenon that he refers to as "the strength of weak ties."

7. Vistnes and Banthin (1997/98) have shown that attitudes toward medical care and risk are an important determinant of the decision to purchase a medigap policy. We include an indicator for whether the household was "satisfied with their health care" in all of our models and include measures of risk tolerance in sensitivity checks reported in the Appendix.

8. The questions are as follows: "Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance it will double your current (family) income and a 50-50 chance it will cut your (family) income by a third. Would you take the new job?" If the respondent answers "yes" to this question, they are asked the following question: "Suppose that the chances were 50-50 that it would double your (family) income, and 50-50 that it would cut it in half. Would you still take the new job?" If they answered "no" to the first question, they are asked: "Suppose that the chances were 50-50 that it would double your (family) income, and 50-50 that it would cut it by 20 percent. Would you then take the new job?"

9. Some of the variables used in our regressions in categorical form (e.g., income and wealth, which are each entered as a group of ten dummy variables in our regression models), have been converted back into continuous variables to provide a more accessible description of the sample.

10. Results are similar using a logit or linear probability model.

11. Results are similar when the “Medicare only” households are dropped from the sample.

12. In addition, one would need a strategy for overcoming the identification problems discussed by Manski (1993).

Table 1. Summary Statistics

	Mean	Minimum	Maximum
Dependent Variables			
Holds a Medigap policy	0.808	0.000	1.000
Enrolled in a Medicare managed care plan	0.132	0.000	1.000
Sociability Indicator			
Sociable	0.894	0.000	1.000
Basic Demographics			
White	0.899	0.000	1.000
Married	0.668	0.000	1.000
High school graduate	0.355	0.000	1.000
Some college	0.205	0.000	1.000
College graduate	0.250	0.000	1.000
Age	75.55 (7.06)	65.00	101.00
Income, Wealth and Employment			
Income (dollars)	14,437 (39,558)	0.00	1,053,000
Wealth (dollars)	172,643 (466,562)	-996,850	9,710,000
Employed	0.066	0.000	1.000
Health Status			
Satisfied with health care	0.056	0.000	1.000
Can walk several blocks	0.840	0.000	1.000
Can climb stairs	0.806	0.000	1.000
Can pick up a dime	0.963	0.000	1.000

Table 1. Summary Statistics (continued)

	Mean	Minimum	Maximum
Diabetes	0.221	0.000	1.000
Cancer	0.236	0.000	1.000
Lung disease	0.159	0.000	1.000
Heart condition	0.374	0.000	1.000
Heart attack	0.053	0.000	1.000
Angina	0.124	0.000	1.000
Stroke	0.121	0.000	1.000
Arthritis	0.736	0.000	1.000
Broken hip	0.021	0.000	1.000
Cataract	0.184	0.000	1.000
Glaucoma	0.066	0.000	1.000
Felt depressed	0.183	0.000	1.000
Felt everything was an effort	0.293	0.000	1.000
Sleep was restless	0.441	0.000	1.000
Felt happy	0.898	0.000	1.000
Felt lonely	0.193	0.000	1.000
Felt sad	0.233	0.000	1.000
Could not get going	0.314	0.000	1.000
Had a lot of energy	0.649	0.000	1.000

Table 1. Summary Statistics (continued)

Medical Care Utilization			
Overnight stay in hospital in past two years	0.455	0.000	1.000
Number of overnight hospital stays in past two years	0.810 (1.482)	0.000	25.000
Stay in nursing home in past two years	0.032	0.000	1.000
Number of doctor visits in past two years	13.53 (19.93)	0.00	700.00
Home health care in past two years	0.145	0.000	1.000

Notes: Standard deviations for continuous variables are in parentheses. Note that many of the variables listed above enter our regressions in a less parametric form. For example, race, marital status, age, income, wealth and employment status are specified as collections of dummy variables, as shown in Tables 2 and 3. They are displayed in a condensed form here to provide a more transparent picture of the sample.

Table 2. Effect of Sociability on the Likelihood of Enrolling in a Medicare Managed Care Plan – Probit Models

	(1)	(2)	(3)	(4)
Sociability Indicator	-0.199	-0.191	-0.197	-0.196
	(0.068)	(0.069)	(0.069)	(0.070)
	[-0.041]	[-0.039]	[-0.040]	[-0.039]
Basic Demographics				
Black	0.537	0.533	0.523	0.527
	(0.086)	(0.089)	(0.091)	(0.092)
	[0.133]	[0.130]	[0.125]	[0.126]
Hispanic	0.209	0.204	0.210	0.219
	(0.130)	(0.130)	(0.133)	(0.136)
	[0.044]	[0.043]	[0.043]	[0.045]
Other race	0.171	0.142	0.102	0.119
	(0.198)	(0.206)	(0.207)	(0.204)
	[0.036]	[0.029]	[0.020]	[0.023]
Separated	-0.588	-0.693	-0.639	-0.664
	(0.361)	(0.350)	(0.357)	(0.356)
	[-0.076]	[-0.082]	[-0.077]	[-0.078]
Divorced	-0.082	-0.136	-0.128	-0.110
	(0.114)	(0.117)	(0.127)	(0.127)
	[-0.015]	[-0.023]	[-0.022]	[-0.019]
Widowed	-0.219	-0.250	-0.227	-0.222
	(0.060)	(0.062)	(0.074)	(0.075)
	[-0.038]	[-0.042]	[-0.038]	[-0.037]
Never married	-0.336	-0.352	-0.324	-0.338
	(0.181)	(0.181)	(0.189)	(0.191)
	[-0.051]	[-0.053]	[-0.048]	[-0.050]
High school graduate	-0.006	-0.020	-0.004	0.000
	(0.068)	(0.068)	(0.069)	(0.070)
	[-0.001]	[-0.004]	[-0.001]	[0.000]
Some college	0.012	0.012	0.032	0.059
	(0.074)	(0.076)	(0.077)	(0.077)
	[0.002]	[0.002]	[0.006]	[0.011]
College graduate	-0.156	-0.132	-0.102	-0.088
	(0.075)	(0.079)	(0.081)	(0.082)
	[-0.028]	[-0.024]	[-0.018]	[-0.016]

Table 2. Effect of Sociability on the Likelihood of Enrolling in a Medicare Managed Care Plan – Probit Models (continued)

	(1)	(2)	(3)	(4)
8 five-year age dummies	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Income, Wealth and Employment				
Income dummies (deciles)	No	Yes	Yes	Yes
Wealth dummies (deciles)	No	Yes	Yes	Yes
7 employment status dummies	No	Yes	Yes	Yes
Health Status				
Satisfied with health care	--	--	0.149 (0.096) [0.030]	0.155 (0.097) [0.031]
Can walk several blocks	--	--	-0.106 (0.082) [-0.020]	-0.085 (0.083) [-0.016]
Can climb stairs	--	--	0.004 (0.071) [0.001]	-0.010 (0.071) [-0.002]
Can pick up a dime	--	--	-0.199 (0.144) [-0.041]	-0.211 (0.152) [-0.043]
11 chronic condition dummies	No	No	Yes	Yes
8 mental status dummies	No	No	Yes	Yes

Table 2. Effect of Sociability on the Likelihood of Enrolling in a Medicare Managed Care Plan – Probit Models (continued)

	(1)	(2)	(3)	(4)
Medical Care Utilization				
Overnight stay in hospital in past two years	--	--	--	0.005 (0.063) [0.001]
Number of overnight hospital stays in past two years	--	--	--	-0.060 (0.023) [-0.011]
Stay in nursing home in past two years	--	--	--	0.068 (0.150) [0.013]
Number of doctor visits in past two years	--	--	--	-0.003 (0.002) [-0.001]
Home health care in past two years	--	--	--	0.230 (0.078) [0.046]
R-squared	0.134	0.143	0.152	0.156
N	6271	6269	6243	6178

Notes: The dependent variable equals "one" if at least one member of the household is enrolled in a Medicare managed care plan. Robust standard errors are in parentheses. Marginal effects are in brackets.

Table 3. Effect of Sociability on the Likelihood of Enrolling in a Medicare Managed Care Plan – Difference-in-Differences Models

	(1)	(2)	(3)	(4)
Sociability Indicator	-0.269 (0.077) [-0.058]	-0.264 (0.078) [-0.056]	-0.271 (0.079) [-0.056]	-0.268 (0.079) [-0.056]
College graduate	-0.415 (0.166) [-0.070]	-0.403 (0.171) [-0.067]	-0.372 (0.170) [-0.061]	-0.353 (0.172) [-0.058]
Sociability Indicator × College graduate	0.291 (0.170) [0.060]	0.304 (0.171) [0.062]	0.303 (0.170) [0.061]	0.296 (0.171) [0.059]
Column-specific controls included	Yes	Yes	Yes	Yes
R-squared	0.135	0.143	0.153	0.157
N	6271	6269	6243	6178

Notes: The dependent variable equals "one" if at least one member of the household is enrolled in a Medicare managed care plan. Robust standard errors are in parentheses. Marginal effects are in brackets.

Table 4. Effect of Sociability on Holdings of More Familiar Financial Products

	Holds Life Insurance Policy				Maintains Checking Account			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Sociability Indicator	0.046 (0.066) [0.011]	0.032 (0.066) [0.008]	0.012 (0.067) [0.003]	0.017 (0.067) [0.004]	0.069 (0.082) [0.008]	0.039 (0.084) [0.004]	0.010 (0.085) [0.001]	0.007 (0.086) [0.001]
Column-specific controls included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.112	0.122	0.132	0.131	0.097	0.131	0.142	0.137
N	6356	6342	6318	6254	6197	6169	6144	5946

Notes: The dependent variable equals "one" if at least one member of the household holds a life insurance policy (81.78 percent of the sample) or maintains a checking account (92.52 percent of the sample), respectively. Robust standard errors are in parentheses. Marginal effects are in brackets.

Table 1A. Effect of Sociability on the Likelihood of Enrolling in a Medicare Managed Care Plan - Sensitivity to Inclusion of HRS Risk Tolerance Measures

	Without Controls for Risk Tolerance				With Risk Tolerance Controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sociability Indicator	-0.303 (0.160) [-0.077]	-0.299 (0.163) [-0.075]	-0.392 (0.161) [-0.097]	-0.391 (0.160) [-0.093]	-0.303 (0.160) [-0.076]	-0.302 (0.163) [-0.076]	-0.392 (0.161) [-0.097]	-0.392 (0.160) [-0.093]
First risk tolerance indicator	--	--	--	--	-0.185 (0.178) [-0.038]	-0.208 (0.170) [-0.041]	-0.189 (0.173) [-0.036]	-0.197 (0.172) [-0.036]
Second risk tolerance indicator	--	--	--	--	0.264 (0.135) [0.065]	0.196 (0.141) [0.047]	0.169 (0.146) [0.038]	0.140 (0.151) [0.030]
Column-specific controls included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.154	0.183	0.217	0.241	0.158	0.186	0.219	0.243
N	1240	1222	1216	1210	1240	1222	1216	1210

Notes: The dependent variable equals "one" if at least one member of the household is enrolled in a Medicare managed care plan. Robust standard errors are in parentheses. Marginal effects are in brackets.

Table 2A. Effect of Sociability on the Likelihood of Medicare Supplementation - Multinomial Logit Models

	Holds Medigap Policy				Enrolled in a Medicare MC plan			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Sociability Indicator	0.001	0.014	0.050	0.050	-0.380	-0.358	-0.349	-0.350
	(0.128)	(0.128)	(0.131)	(0.132)	(0.159)	(0.161)	(0.164)	(0.165)
	[0.017]	[0.018]	[0.024]	[0.024]	[-0.020]	[-0.019]	[-0.021]	[-0.021]
Basic Demographics								
Black	-0.734	-0.641	-0.584	-0.589	0.426	0.497	0.529	0.524
	(0.151)	(0.157)	(0.161)	(0.163)	(0.180)	(0.187)	(0.193)	(0.196)
	[-0.160]	[-0.143]	[-0.133]	[-0.134]	[0.072]	[0.071]	[0.071]	[0.071]
Hispanic	0.030	-0.030	0.054	0.048	0.393	0.339	0.397	0.407
	(0.292)	(0.293)	(0.288)	(0.288)	(0.317)	(0.317)	(0.320)	(0.325)
	[-0.014]	[-0.020]	[-0.011]	[-0.012]	[0.020]	[0.020]	[0.019]	[0.020]
Other race	-0.196	-0.146	-0.119	-0.141	0.120	0.090	0.048	0.070
	(0.338)	(0.343)	(0.342)	(0.345)	(0.423)	(0.443)	(0.422)	(0.418)
	[-0.036]	[-0.026]	[-0.020]	[-0.024]	[0.015]	[0.011]	[0.007]	[0.009]
Separated	-0.242	-0.092	-0.007	-0.010	-1.358	-1.364	-1.165	-1.193
	(0.571)	(0.567)	(0.599)	(0.599)	(0.870)	(0.875)	(0.882)	(0.892)
	[0.017]	[0.040]	[0.045]	[0.046]	[-0.053]	[-0.058]	[-0.053]	[-0.054]
Divorced	-0.082	0.068	0.081	0.111	-0.221	-0.211	-0.187	-0.129
	(0.259)	(0.255)	(0.236)	(0.240)	(0.296)	(0.299)	(0.305)	(0.306)
	[-0.004]	[0.018]	[0.019]	[0.021]	[-0.007]	[-0.012]	[-0.012]	[-0.010]
Widowed	0.033	0.120	0.151	0.153	-0.428	-0.421	-0.355	-0.356
	(0.096)	(0.102)	(0.125)	(0.126)	(0.140)	(0.146)	(0.176)	(0.178)
	[0.022]	[0.034]	[0.036]	[0.036]	[-0.021]	[-0.024]	[-0.023]	[-0.023]

Table 2A. Effect of Sociability on the Likelihood of Medicare Supplementation - Multinomial Logit Models (continued)

	Holds Medigap Policy				Enrolled in a Medicare MC plan			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Never married	0.081	0.209	0.208	0.206	-0.609	-0.537	-0.525	-0.554
	(0.268)	(0.272)	(0.284)	(0.289)	(0.404)	(0.409)	(0.426)	(0.431)
	[0.036]	[0.052]	[0.051]	[0.052]	[-0.031]	[-0.033]	[-0.033]	[-0.034]
High school graduate	-0.202	-0.212	-0.196	-0.210	-0.194	-0.233	-0.187	-0.184
	(0.127)	(0.130)	(0.129)	(0.132)	(0.164)	(0.166)	(0.166)	(0.168)
	[-0.023]	[-0.022]	[-0.021]	[-0.023]	[-0.001]	[-0.002]	[-0.001]	[0.000]
Some college	-0.182	-0.209	-0.219	-0.232	-0.133	-0.160	-0.126	-0.082
	(0.136)	(0.139)	(0.141)	(0.143)	(0.175)	(0.179)	(0.182)	(0.184)
	[-0.023]	[-0.025]	[-0.028]	[-0.031]	[0.001]	[0.001]	[0.003]	[0.006]
College graduate	-0.188	-0.240	-0.228	-0.236	-0.470	-0.472	-0.397	-0.376
	(0.135)	(0.139)	(0.144)	(0.146)	(0.179)	(0.187)	(0.193)	(0.195)
	[-0.011]	[-0.018]	[-0.018]	[-0.020]	[-0.013]	[-0.012]	[-0.009]	[-0.008]
8 five-year age dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income, Wealth and Employment								
Income dummies (deciles)	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Wealth dummies (deciles)	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Table 2A. Effect of Sociability on the Likelihood of Medicare Supplementation - Multinomial Logit Models (continued)

	Holds Medigap Policy				Enrolled in a Medicare MC plan			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
7 employment status dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Health Status								
Satisfied with health care	--	--	0.030	0.023	--	--	0.294	0.290
			(0.180)	(0.181)			(0.216)	(0.218)
			[-0.007]	[-0.008]			[0.012]	[0.012]
Can walk several blocks	--	--	0.139	0.143	--	--	-0.099	-0.058
			(0.134)	(0.136)			(0.188)	(0.191)
			[0.024]	[0.023]			[-0.010]	[-0.008]
Can climb stairs	--	--	-0.255	-0.256	--	--	-0.185	-0.211
			(0.119)	(0.120)			(0.167)	(0.168)
			[-0.029]	[-0.028]			[0.002]	[0.000]
Can pick up a dime	--	--	-0.239	-0.203	--	--	-0.609	-0.584
			(0.254)	(0.261)			(0.354)	(0.381)
			[-0.010]	[-0.006]			[-0.019]	[-0.019]
11 chronic condition dummies	No	No	Yes	Yes	No	No	Yes	Yes
8 mental status dummies	No	No	Yes	Yes	No	No	Yes	Yes

Table 2A. Effect of Sociability on the Likelihood of Medicare Supplementation - Multinomial Logit Models (continued)

	Holds Medigap Policy				Enrolled in a Medicare MC plan			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Medical Care Utilization								
Overnight stay in hospital in past two years	--	--	--	0.004 (0.104) [0.000]	--	--	--	0.008 (0.146) [0.000]
Number of overnight hospital stays in past two years	--	--	--	-0.010 (0.029) [0.003]	--	--	--	-0.109 (0.049) [-0.005]
Stay in nursing home in past two years	--	--	--	0.441 (0.288) [0.043]	--	--	--	0.512 (0.389) [0.006]
Number of doctor visits in past two years	--	--	--	0.002 (0.002) [0.000]	--	--	--	-0.004 (0.004) [0.000]
Home health care in past two years	--	--	--	-0.047 (0.144) [-0.021]	--	--	--	0.348 (0.189) [0.018]
R-squared	0.117	0.126	0.138	0.141	0.117	0.126	0.138	0.141
N	6426	6424	6398	6333	6426	6424	6398	6333

Notes: The estimates are from a multinomial logit model with three categories: enrolled in a Medicare managed care plan (13.2 percent of the sample); holds a medigap policy (80.8 percent of the sample); has coverage exclusively from Medicare (the omitted category; 6 percent of the sample). Robust standard errors are in parentheses. Marginal effects are in brackets.

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