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The role of consumer knowledge of insurance benefits in the demand for preventive health care among the elderly

Stephen T. Parente[a,b,*], David S. Salkever[c,d] and Joan DaVanzo[e]
[a] *Department of Health Care Management, Carlson School of Management, University of Minnesota, Minneapolis, Minnesota, USA*
[b] *Project HOPE Center for Health Affairs, USA*
[c] *Department of Health Policy and Management, Johns Hopkins University, Baltimore, Maryland, USA*
[d] *NBER, USA*
[e] *The Lewin Group, Falls Church, Virginia, USA*

Summary

In 1992, the United States Centers for Medicare and Medicaid Services (CMS) introduced new insurance coverage for two preventive services – influenza vaccinations and mammograms. Economists typically assume transactions occur with perfect information and foresight. As a test of the value of information, we estimate the effect of consumer knowledge of these benefits on their demand. Treating knowledge as endogenous in a two-part model of demand, we find that consumer knowledge has a substantial positive effect on the use of preventive services. Our findings suggest that strategies to educate the insured Medicare population about coverage of preventive services may have substantial social value. Copyright © 2004 John Wiley & Sons, Ltd.

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Introduction

Although economists typically assume that economic transactions occur with perfect knowledge, consumers in health care markets often demand medical care with very limited information on product characteristics and prices, and frequently rely on providers to act as their agents [1]. Educational interventions to increase consumers' knowledge of the costs and/or probable benefits of medical care are, however, feasible. In 1992, the United States Health Care Financing Administration (HCFA) introduced coverage for Medicare beneficiaries of two preventive services not previously covered – influenza vaccinations and mammograms. Since then, HCFA, which was recently renamed the Center for Medicare and Medicaid Services (CMS), has used multiple communication strategies to inform beneficiaries of these benefits, such as employing Medicare carriers to promote the use of preventive care in order to reduce the risk of illness or avoidable hospitalization.

Previous research suggests that educational interventions can translate into increased use of services in general, and of preventive services in particular. Using data from a household survey

*Correspondence to: Department of Health Care Management, Carlson School of Management, University of Minnesota, 321/19th Avenue South, Room 3-149, Minneapolis, MN 55455, USA. E-mail: sparente@csom.umn.edu

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conducted in the mid-1970s, Kenkel [2] measured consumers' health knowledge by responses to a set of questions about the symptoms associated with diabetes, heart disease, cancer and tuberculosis. He found that better informed consumers were significantly more likely to visit a physician. Hsieh and Lin [3] examined the effect of information on demand for preventive care (tests for blood pressure and blood sugar levels, and urinalysis) among elderly persons in Taiwan. Their measures of information were based on responses to questions about symptoms associated with high blood pressure and diabetes, the type of tests necessary to detect diabetes, and the consequences of poor diabetes or high blood pressure management. Their results generally supported the notion that better informed respondents were more likely to obtain the preventive services they studied.

New evidence suggests that influenza vaccinations (commonly referred to in the United States as flu shots) and mammograms among the elderly increased between 1992 and 1997. In 1997, 62% of Medicare beneficiaries reported that they obtained a flu shot compared to 44% in 1992, and 43% of women reported obtaining a mammogram compared to 19% in 1992 [4]. While a detailed analysis of these increases, and the possible role of consumer knowledge and education, has yet to be carried out, the latest empirical analysis on the factors affecting influenza vaccination by Mullahy [5] argues that an understanding of the role education and the knowledge of medical benefits play in the receipt of a flu shot would be a valuable extension of earlier research.

Previous studies have not specifically addressed the impact of knowledge of benefits on service utilization, but recent data indicate that Medicare enrollees are in general poorly informed about their health insurance benefits. CMS's 1996–1998 Market Research for Beneficiaries project[a] identified multiple deficiencies in beneficiaries' basic knowledge of the Medicare program [6]. Although most beneficiaries know about the major features of Medicare, they tended to have inadequate knowledge of services that are infrequently used (such as long term care, second surgical opinion, or coverage of durable medical equipment) or recently implemented benefits (such as influenza and pneumonia vaccinations). These findings are supported by McCall *et al*. [7] who surveyed Medicare beneficiaries in six states and reported a low level of knowledge of Medicare benefits and supplemental policy benefits. These authors also found that respondents were more likely to be aware of benefits for the services they use most, including eyeglasses, physician care, and prescription drugs, rather than infrequently used services such as hospital or nursing home care. It is also worth noting that other studies of the general population (rather than just Medicare enrollees) also document gaps and misinformation in consumers' reported knowledge of health plans and entitlement programs [8,9].

In this paper, we explicitly examine the impact of elderly persons' knowledge of Medicare benefits on the demand for preventive health care using supplemental questions from Round 18 of the Medicare Current Beneficiary Survey (MCBS) regarding beneficiary knowledge of Medicare. The aim of this analysis is to identify the marginal effect of such benefit knowledge on demand in order to better value future initiatives to create a more informed health care consumer. In the remainder of this paper, we describe our conceptual model, methods, study population, estimation results, interpretations of our empirical findings, and conclusions.

Conceptual model

We use a simple conceptual framework of consumer demand for preventive care to motivate and interpret our empirical work. In this framework, the consumer faces two uncertain states of the world in which she is either exposed or not exposed to a preventable disease. Corresponding probabilities are π_E and π_N $(= 1 - \pi_E)$. The consumer's utility function in each state, i, is $U \times (H_i, Z_i; X)$ $(i = E, N)$, where H_i is realized health status, Z_i is spending on all other goods and services except the prevention of the preventable disease, and X is a vector of socio-demographic characteristics describing the consumer. H_N is health status in the absence of the disease and we let λ denote the decline in health status due to the disease, Y denote consumer income, and C denote the cost of preventive services. Assuming that the consumer maximizes expected utility and that preventive services reduce the probability of disease occurrence in the event of exposure by the factor $(1 - \theta)$ (with $0 \leqslant \theta \leqslant 1$), the consumer will choose to obtain preventive services if

$$\theta\pi_{\mathrm{E}} \cdot U(H_N - \lambda, Y - C; Z) + (1 - \theta\pi_E) \times U(H_N, Y - C; Z) > \pi_E \cdot U(H_N - \lambda, Y; Z) + (1 - \pi_E) \cdot U(H_N, Y; Z) \quad (1)$$

Taking a first-order Taylor series approximation around (H_N, Y) and subtracting common terms from both sides and rearranging terms, (1) becomes

$$-(1 - \theta\pi_E)\lambda(\partial U/\partial H) > C(\partial U/\partial Y) \quad (2)$$

This simply states that the consumer obtains preventive services when the expected utility gain from reduced risk of the disease exceeds the utility loss from the financial cost of the services.

The simple framework highlights several ways in which the level of consumer knowledge can impact the decision to obtain preventive services. First, in the absence of knowledge that the service is a fully covered benefit, the consumer will overestimate C. Second, the consumer may underestimate their risk of exposure (π_E) and/or the severity of the disease (λ). Third, the uninformed consumer may underestimate the effectiveness of the service in preventing the disease $(1 - \theta)$. In formal terms, the dependence of the consumer's decision upon the level of knowledge, denoted by K, can be represented in (1) and (2) above by making the variables C, λ, θ, and π_E functions of K.

While this simple model only allows socio-demographic characteristics (the vector X) to influence the consumer's decision via preferences, we recognize that other channels for these influences may in fact be operative. The level of knowledge about key variables $(C, \lambda, \theta, \pi_E)$ may be correlated with some elements of X. Exposure risk (λ, θ, π_E) may also vary with socio-demographic characteristics. To the extent that beneficiaries in varying circumstances differ in the quality of medical care they can access, they may also face differing levels of λ and θ.

In the empirical implementation of our model, consumer perceptions of $C, \lambda, \theta, \pi_E$ are not directly observable determinants of preventive service use. We seek to control for variations in these magnitudes across the sample by including exogenous variables relating to consumer health status and epidemiologic risk factors, access to care, income, other socio-demographic characteristics, and consumer knowledge of Medicare coverage for preventive services. The impact of the consumer knowledge variable, which is the primary focus of our analysis, is largely a reflection of the influence of C on consumer decisions. Those who know that the service is covered are aware that the out-of-pocket cost for the service itself is zero and those who do not know this overestimate this cost. While this suggests that the coefficient for the consumer knowledge variable in our empirical estimates is mainly a price effect on demand, we recognize that the knowledge variable may also be correlated with higher estimates of λ or π_E, or lower estimates of θ, because the educational interventions that promoted benefit knowledge also increased awareness of risks and consequences of exposure and efficacy of prevention. As discussed below, we also follow previous researchers in allowing for the possibility that the consumer knowledge variable is itself endogenous and therefore employ an instrumental variables estimation method.

Data sources

The principal data source used in our analysis is the annual MCBS. Administered to a nationally representative sample of Medicare beneficiaries, the MCBS obtains information from beneficiaries on socio-demographic characteristics, use of medical care, and indicators of health status and illness. Other respondent characteristics obtained in the survey include education, household composition, health status, income, and supplemental insurance coverage. The database also includes the Medicare claims records for respondents. These claims records describe the exact health services provided and reimbursed and serve to supplement the beneficiary's recollection of whether certain medical services, such as mammography, were provided. Once participating in the survey, a beneficiary is surveyed three times a year for an in-depth personal interview for three years. Beneficiaries who die during the course of their survey participation are replaced in the following year of the survey to keep the average number of survey participants at roughly 14 000 beneficiaries.

In this analysis, we used data on respondent characteristics from Round 16 of the MCBS (the 'health access survey') administered in Fall, 1996. Information on respondents' knowledge of benefits was obtained from supplemental questions from Round 18 of the MCBS, which was administered later in summer 1997. The questions included a short quiz to test beneficiary knowledge of the Medicare, as well as questions regarding the beneficiary's use of the Medicare Handbook and their access to communication technologies. We use five quiz questions from Round 18. (These questions are given in our Appendix A.) The first two ask if flu shot and mammography are covered services. The remaining three questions test knowledge of Medicare coverage of physical examinations, rules on provider payment and assignment, and rights to appeal a payment decision.

An additional data component for the analysis was claims data for all beneficiaries from the Medicare 5% Part B physician file for calendar year 1996. From these data, we computed utilization rates for flu shots and mammography for each 5-digit zip code. (Denominators for these rates were the total number of beneficiaries reporting any claims in each zip code in 1996.) These rates were matched by zip codes of residence to the beneficiaries in our analysis and were used as explanatory variables to control for possible neighborhood effects. Differences in 'neighborhood' use rates may be indicative of patterns of diffusion of information [10] since consumers may learn about their benefits from neighbors who used the service in question. These rates could also be capturing zip-code-specific variations in access to services or variations in preferences that we cold not directly observe.

The binary dependent variables in our analysis, for obtaining a mammogram and a flu shot, were constructed from one year of claims data (1 September 1997 to 31 August 1998) following the end of interviewing for Round 18 of the MCBS survey (in August 1997). (For respondents in our study whose participation in the MCBS ended before 31 August 1998, we obtained their additional claims data from CMS to complete our 12-month follow-up period.) Thus our dependent variable measures of utilization were collected subsequent to our measures of consumer knowledge.

We also obtained binary indicators of prior use for mammogram and flu shots for MCBS respondents pertain to calendar 1995. These were based on self-report data in the 1995 MCBS Cost and Use file.

Estimation methods and model specification

In estimating the effects of consumer knowledge on service use, previous researchers [2,3] have recognized the potential problem that estimated knowledge coefficients are contaminated by simultaneity bias. In particular, this could arise if persons with stronger preferences for using a particular service gain knowledge about that service and its coverage from their providers and from prior utilization experiences. Following Kenkel, and Hsieh and Lin, we address this problem via the use of instrumental variables for our measures of benefit knowledge.

In particular, consumer knowledge of benefits is measured directly by a binary indicator for the correct response to the coverage of flu shot or mammogram quiz questions. Indicators of responses to the other quiz questions, relating to Medicare program administration, were used as instrumental variables for these knowledge of benefits measures. This procedure was based on the rationale that enrollees with a good knowledge of the Medicare program are likely to know about coverage of preventive health care while a 'taste' for preventive care will not be correlated with general Medicare program knowledge. As in Mullahy's recent work on flu shots, we estimate a two-stage model with binary dependent variables. The estimated models take the form

$$K_i = a_0 + a_1 Y_i + P_i + u_i \tag{3}$$

$$D_i = b_0 + b_1 Y_i + b_2 K_i + v_i \tag{4}$$

where K is the binary indicator of benefit knowledge for beneficiary i P_i is a two-element vector of binary indicators of general Medicare program knowledge, D_i is the binary indicator of preventive service use, Y_i is a vector of exogenous determinants of preventive service demand, and u_i *and* v_i are random errors that may be correlated. The explanatory variables in the vector Y_i include determinants of the beneficiary's demand such as income, supplementary insurance coverage, education, and demographic characteristics. Measures of beneficiary health characteristics are included on the assumption that these will affect the beneficiary's perceptions of exposure risk, severity of illness consequences, and preventive service effectiveness. Neighborhood use measures are included to account for geographic differences in access which may be correlated with time costs of obtaining preventive services (a component of C in our conceptual model) and diffusion of benefit knowledge. Finally, we also include a prior use variable based on the beneficiary's self-reported prior year use of the preventive service examined.

Prior use will increase consumer knowledge through experience. It will also proxy for unmeasured 'taste' factors that are stable over time. Thus, we view the inclusion of prior use as providing a more stringent test of the pure effect of benefit knowledge on demand. More specific definitions for these variables are given in Table 1.

Equations (3) and (4) are estimated via two-stage least squares with Huber–White robust standard-error estimates for coefficients. The properties of this estimation method for simultaneous equations with binary dependent variables have previously been described by Heckman and MaCurdy [11]. A recent example of applying this method in a closely related context is Mullahy [5]. We note that concern over several deficiencies of least-squares estimation of linear probability models should be relatively minor in our application. In particular, robust standard-error estimation allows for heteroscedasticity, while specification error due to the assumption of a linear functional form should not be a major problem with dependent variables whose mean values are far from the extremes of the 0–1 interval.

Study population characteristics

The core analytic sample for the analysis contains complete data for beneficiaries age 65 and older who were living in the community (i.e., who were not living in a short- or long-term care facility) and who answered Rounds 16–18 of the MCBS. We excluded respondents from this subset who had missing data for the dependent variables or key beneficiary characteristics, such as income information. Respondents enrolled in Medicare managed care health plans were also included provided their health service utilization data, which would normally be abstracted from administrative claims data, was not missing. An analysis of excluded respondents did not reveal significant economic or demographic differences from the non-excluded respondents. Although income differences could not be determined directly for the excluded respondents, a slightly higher percentage of beneficiaries with Medicaid eligibility, and a lower percentage of beneficiaries with higher education levels, were in the non-excluded (i.e., study) sample.

Table 1 summarizes the two study samples, one for the entire population to model flu shot demand and the other restricted to women for modeling mammography screening demand. The largest age group in the sample is the 65–74 year olds, who make up 41% of the total sample. A slight majority of beneficiaries are women (51%). About 83% of Medicare beneficiaries in the sample are White non-Hispanic, with African Americans (non-Hispanic) comprising the second largest racial group (9%), and Hispanics making up 6% of the sample. Many Medicare beneficiaries have low incomes, with the largest income group being \$15 000 or less (about 46% of the sample). About 41% of the sample has not completed high school. Over half of beneficiaries live with their spouse (53%). Approximately one-third of the sample live in the south (35%), and three-quarters live in a metropolitan area (71%). Only 10% of the sample are Medicaid recipients and nearly three quarters of the sample (71%) have some supplemental coverage (e.g., Medigap) purchased directly or provided by a former employer.

A majority of beneficiaries reported they were in excellent, very good, or good health (78%). However, 38% have been told they have a chronic heart condition, 18% have been told they have cancer, 15% have diabetes, 13% have emphysema, asthma, or COPD, and 11% have had a stroke. About 41% of beneficiaries have a visual impairment (have some or a lot of trouble seeing) or are blind, while about 45% are hard of hearing (have some or a lot of trouble hearing) or are deaf.

Estimation results

Table 2 presents the results of the first-stage regressions on (1) flu shot benefit knowledge for the entire study population and (2) women's knowledge of the mammography screening benefit. General Medicare knowledge is found to be positively and significantly related to flu shot benefit knowledge. The same is true for prior use of flu shots. Those likely to have greater knowledge of the benefit are those with supplemental coverage and those living in rural areas. Given that supplemental carriers provide another source of information about health benefits, this result is not surprising. Beneficiaries residing in rural areas may be less inundated with information than urban populations, and may be better able to attend the

Table 1. Variable names and descriptive statistics

Variable	Beneficiary characteristic definition	Total ($N = 7473$) Mean	Total ($N = 7473$) Standard deviation	Female only ($N = 4296$) Mean	Female only ($N = 4296$) Standard deviation
Dependent variables					
FLUSHOT	Received Medicare reimbursed flu shot = 1, else 0	0.387	0.487	—	—
MAMMOGRM	Received mammogram = 1, else 0	—	—	0.285	0.451
Benefit knowledge variables					
FLUKNOW	Knowledge of flu shot benefit = 1, else 0	0.775	0.418	—	—
MAMKNOW	Knowledge of mammography benefit = 1, else 0	—	—	0.674	0.469
Prior use variables					
PRIORFLU	Received flu shot in prior year = 1, else 0	0.653	0.476	—	—
PRIORMAM	Received mammogram in prior year = 1, else 0	—	—	0.406	0.491
Knowledge instrument variables					
MCAREKNOW_A	Knowledge of assigned provider rule = 1, else 0	0.674	0.469	0.671	0.470
MCAREKNOW_B	Knowledge of appeal process = 1, else 0	0.760	0.427	0.739	0.439
Neighborhood variables					
FLU NEIGBOR	Beneficiary's Zip code average flu shot rate	0.887	0.183	—	—
MAM NEIGBOR	Beneficiary's Zip code average mammography rate	—	—	0.198	0.227
Other independent variables					
WHITE	*Reference race category*				
HISPANIC	Race is Hispanic = 1, else 0	0.062	0.241	0.059	0.236
BLACK	Race is black = 1, else 0	0.088	0.283	0.095	0.293
OTHER RACE	Race is not white, Hispanic or black = 1, else 0	0.018	0.135	0.019	0.138
DUAL ELLIGIBILITY	Dually eligible for Medicaid = 1, else 0	0.101	0.301	0.131	0.337
MEDIGAP	Supplemental insurance = 1, else 0	0.711	0.453	0.703	0.457
RURAL	Outside metropolitan statistical area = 1, else 0	0.295	0.456	0.292	0.455
VISION PROBLEM	Vision problem = 1, else 0	0.406	0.491	0.424	0.494
HEARING PROBLEM	Hearing problem = , else 0	0.453	0.498	0.394	0.489
EDUCATION LEVEL1	*Reference education category*				
EDUCATION LEVEL2	Completed 5th grade–8th grade = 1, else 0	0.167	0.389	0.164	0.370
EDUCATION LEVEL3	Completed 9th grade–11th grade = 1, else 0	0.165	0.365	0.183	0.387
EDUCATION LEVEL4	Completed 12th grade = 1, else 0	0.320	0.464	0.337	0.473
EDUCATION LEVEL5	Education beyond 12th grade = 1, else 0	0.272	0.438	0.249	0.433
EXC/GOOD HEALTH	Excellent to good health = 1, else 0	0.778	0.412	0.769	0.421
NO ADLS	*Reference ADL category*				
ADL1TO3	1–3 ADL restrictions = 1, else 0	0.158	0.369	0.189	0.392
ADL4TO5	4–5 ADL restrictions = 1, else 0	0.032	0.181	0.039	0.193
IADLTELE	Unable to use telephone = 1, else 0	0.072	0.251	0.059	0.236
IADLBILS	Unable to pay bills = 1, else 0	0.069	0.269	0.079	0.270
MALE	Male gender = 1, else 0	0.422	0.494	—	—
NORTHEAST	*Reference region category*				
NORTH CENTRAL	Resides North Central US State = 1, else 0	0.248	0.428	0.243	0.429
SOUTH	Resides in Southern US State = 1, else 0	0.350	0.481	0.360	0.480

Table 1 (*continued*)

Variable	Beneficiary characteristic definition	Total ($N = 7473$) Mean	Total Standard deviation	Female only ($N = 4296$) Mean	Female only Standard deviation
WEST	Resides in Western US State = 1, else 0	0.206	0.399	0.206	0.405
PUERTO RICO	Resides in Puerto Rico = 1, else 0	0.016	0.111	0.015	0.122
AGE6574	*Reference age category*				
AGE7584	Aged 75–84 years = 1, else 0	0.408	0.492	0.425	0.494
OVER85	Over aged 85 years = 1, else 0	0.138	0.369	0.158	0.365
INCOME LEVEL1	*Reference income category*				
INCOME LEVEL2	Income level is \$15 001–\$30 000, else 0	0.334	0.472	0.299	0.458
INCOME LEVEL3	Income level is \$30 001 or more, else 0	0.215	0.411	0.158	0.365
HEART	Heart disease history = 1, else 0	0.375	0.484	0.360	0.480
STROKE	Stroke history = 1, else 0	0.105	0.307	0.105	0.306
CANCER	Cancer history = 1, else 0	0.172	0.377	0.174	0.379
DIABTS	Diabetes history = 1, else 0	0.151	0.358	0.145	0.352
EMPHYS	Emphysema history = 1, else 0	0.132	0.338	0.120	0.325
MARRY	Married = 1, else 0	0.534	0.499	0.376	0.484
HOUSEHOLD COMP	Total number of individuals in household	1.912	0.980	1.802	1.029

information they do receive. We may also be observing the impact of information campaigns conducted by CMS, the American Association of Retired Persons, and other social and civic organizations with high participation in rural regions, such as the Rotary Club and Lions Club. Those residing in the South are more likely to know about the benefit than those in the Northeast. Those with a heart condition are more likely to be knowledgeable about the benefit as well. Since heart disease can require a significant interaction with health care delivery and finance systems, spillover knowledge to basic preventive care is not surprising. Finally beneficiaries who are married are also more knowledgeable about flu shots. Two explanations for this result may be that a spouse is another information source, as well as a direct incentive to keep one's partner healthy. Those less likely to know about the benefit include blacks and males.

A number of the results regarding women's knowledge of mammography screening are similar to those found for flu shot benefit knowledge. The factors with the strongest positive effects on knowledge of the mammography benefit are again good knowledge of general Medicare program rules and prior use of mammography. Significant positive effects are again observed for Medigap coverage and for residence in the South. Other features of the results do not parallel the findings for flu shot knowledge. Blacks and Hispanics are significantly more likely to know about the mammography benefit, as are persons with Medicaid coverage. Older beneficiaries are significantly less likely to know about the mammography benefit. There is also stronger evidence of regional differences in benefit knowledge. One of the largest mammography benefit knowledge marginal effects was associated with women residing in Puerto Rico, which again suggests the importance or regional information sources or campaigns. There is also a positive relationship for women with a history of cancer, which may reflect increased concern with cancer prevention.

The OLS and 2SLS second stage estimation results for flu shot and mammography screening demand are presented in Tables 3 and 4, respectively. Benefit knowledge for each of the two preventive services and prior use had strongly significant impacts on service use in both OLS and 2SLS models. Comparison of the 2SLS and OLS results indicates that OLS tends to yield a downward-biased estimate of the impact of knowledge on use. This finding is somewhat surprising but could be explained, at least in part, by the possibility that the prior use variable accounts for much of the positive correlation between unobservables that increase benefit knowledge and unobservables that predispose to use of services. In addition, note that in both the flu shot

Table 2. First stage regression results of factors explaining flu shot and mammography knowledge

Explanatory variable	FLUKNOW OLS Coef.	*T*-stat	MAMKNOW OLS Coef.	*T*-stat
INTERCEPT	**0.407**	*11.280*	**0.275**	*6.160*
MCAREKNOW_A	0.126	*12.170*	**0.149**	*9.650*
MCAREKNOW_B	0.173	*14.770*	**0.175**	*10.350*
PRIORFLU	0.183	*18.730*	—	—
PRIORMAM	—	—	**0.169**	*12.020*
NEIGHBOR	−0.009	*−0.370*	−0.031	*−1.040*
HISPANIC	0.036	*1.560*	**0.075**	*2.150*
BLACK	**−0.048**	*−2.760*	**0.049**	*1.960*
OTHER RACE	0.013	*0.380*	−0.043	*−0.870*
DUAL ELLIGIBILITY	0.020	*1.120*	**0.054**	*2.190*
MEDIGAP	**0.053**	*4.510*	**0.063**	*3.520*
RURAL	**0.037**	*3.550*	−0.010	*−0.650*
VISION PROBLEM	−0.017	*−0.830*	−0.006	*−0.170*
HEARING PROBLEM	0.010	*0.470*	0.044	*1.370*
EDUCATION LEVEL2	−0.002	*−0.110*	0.058	*1.830*
EDUCATION LEVEL3	−0.023	*−1.080*	**0.079**	*2.380*
EDUCATION LEVEL4	−0.002	*−0.250*	**−0.032**	*−0.220*
EDUCATION LEVEL5	0.013	*1.380*	0.012	*0.850*
EXC/GOOD HEALTH	−0.008	*−0.660*	−0.009	*−0.520*
ADL1TO3	0.004	*0.300*	−0.031	*−1.670*
ADL4TO5	0.038	*1.340*	−0.027	*−0.690*
IADLTELE	−0.010	*−0.520*	0.008	*0.260*
IADLBILS	−0.006	*−0.270*	**−0.070**	*−2.420*
MALE	**−0.062**	*−6.180*	—	—
NORTH CENTRAL	0.027	*1.870*	0.021	*0.990*
SOUTH	**0.037**	*2.740*	**0.043**	*2.150*
WEST	0.010	*0.680*	**0.074**	*3.320*
PUERTO RICO	0.073	*1.720*	**0.131**	*2.02*
AGE7584	−0.007	*−0.690*	**−0.032**	*−2.090*
OVER85	−0.023	*−1.530*	**−0.075**	*−3.390*
INCOME LEVEL2	0.001	*0.090*	0.011	*0.640*
INCOME LEVEL3	−0.014	*−0.930*	0.004	*0.170*
HEART	**0.028**	*2.850*	0.024	*1.610*
STROKE	−0.025	*−1.640*	−0.025	*−1.130*
CANCER	−0.003	*−0.220*	0.030	*1.680*
DIABTS	0.023	*1.780*	**0.060**	*3.050*
EMPHYS	0.007	*0.490*	0.000	*0.000*
MARRY	**0.036**	*3.180*	−0.007	*−0.420*
HOUSEHOLD COMP	**−0.010**	*−2.020*	−0.001	*−0.110*
Adjusted R^2	0.1526		0.147	
F-statistic	37.37		21.61	
N	7473		4296	

Notes: Estimates in bold are significant at $P < 0.05$ or less.

and mammography 2SLS models Basmann's [12] test fails to reject our overidentifying exclusion restrictions.

Since the two preventive services are covered with no out-of-pocket cost to the consumer, the interpretation of the strongly positive results for the Medigap and Medicaid dummies (for both services) and for the high income dummy (in the case of mammography) is not the usual straightforward confirmation of negative own-price and positive income effects on demand. An alternative hypothesis concerning insurance effects is that

Table 3. Regression results for flu shot benefit knowledge and flu shot demand

Explanatory variable	OLS coefficient	*T*-stat	Instrumental variables 2SLS coefficient	*T*-stat
INTERCEPT	**−0.129**	*−3.140*	**−0.176**	*−3.680*
FLUKNOW	**0.092**	*7.280*	**0.182**	*3.770*
PRIORFLU	**0.316**	*27.920*	**0.299**	*20.470*
NEIGHBOR	0.029	*1.03*	0.028	*1*
HISPANIC	**−0.084**	*−3.270*	**−0.084**	*−3.250*
BLACK	**−0.060**	*−3.080*	**−0.054**	*−2.710*
OTHER RACE	−0.052	*−1.350*	−0.052	*−1.330*
DUAL ELLIGIBILITY	**0.111**	*5.420*	**0.109**	*5.330*
MEDIGAP	**0.209**	*15.610*	**0.202**	*14.530*
RURAL	**0.060**	*5.110*	**0.056**	*4.700*
VISION PROBLEM	−0.004	*−0.190*	−0.004	*−0.170*
HEARING PROBLEM	−0.008	*−0.350*	−0.012	*−0.480*
EDUCATION LEVEL2	0.006	*0.260*	0.003	*0.130*
EDUCATION LEVEL3	−0.005	*−0.220*	−0.007	*−0.290*
EDUCATION LEVEL4	0.007	*0.640*	0.007	*0.670*
EDUCATION LEVEL5	0.018	*1.690*	0.017	*1.550*
EXC/GOOD HEALTH	0.014	*0.990*	0.013	*0.970*
ADL1TO3	−0.023	*−1.490*	−0.023	*−1.520*
ADL4TO5	−0.063	*−1.950*	**−0.066**	*−2.060*
IADLTELE	−0.008	*−0.380*	−0.008	*−0.350*
IADLBILS	0.016	*0.680*	0.016	*0.690*
MALE	−0.004	*−0.330*	0.002	*0.160*
NORTH CENTRAL	0.030	*1.860*	0.027	*1.650*
SOUTH	0.017	*1.130*	0.013	*0.830*
WEST	**−0.105**	*−6.170*	**−0.107**	*−6.270*
PUERTO RICO	0.024	*0.490*	0.015	*0.300*
AGE7584	0.019	*1.670*	0.019	*1.720*
OVER85	0.017	*1.010*	0.021	*1.230*
INCOME LEVEL2	0.001	*0.040*	−0.001	*−0.080*
INCOME LEVEL3	0.012	*0.700*	0.012	*0.700*
HEART	**0.024**	*2.180*	0.021	*1.860*
STROKE	0.003	*0.170*	0.005	*0.300*
CANCER	**0.044**	*3.250*	**0.044**	*3.250*
DIABTS	−0.009	*−0.580*	−0.011	*−0.730*
EMPHYS	0.016	*1.070*	0.015	*0.980*
MARRY	0.006	*0.440*	0.001	*0.100*
HOUSEHOLD COMP	0.004	*0.730*	0.005	*0.860*
Adjusted R^2	0.1994		0.19503	
F-statistic	52.71		51.29	
N	7473		7473	
Pr, Test of Overid			0.4303	

cross-price effects on preventive service demand are positive. Beneficiaries who use more curative services (because of lower out-of-pocket price) may also be more likely to receive recommendations from their physicians to obtain preventive services. In the case of influenza vaccinations, complementarity in demand could also arise from joint time costs: the time and inconvenience of obtaining a vaccination are greatly reduced if it is received at the same time and in the same provider location in which curative services are received. Both of these arguments could also account for

Table 4. Regression results for mammography benefit knowledge and mammography screening demand

Explanatory variable	OLS coefficient	T-stat	Instrumental variables 2SLS coefficient	T-stat
INTERCEPT	0.082	1.950	**0.032**	0.670
MAMKNOW	**0.098**	7.020	**0.215**	3.950
PRIORMAM	**0.195**	14.370	**0.175**	10.710
NEIGHBOR	**−0.056**	−1.980	−0.050	−1.770
HISPANIC	0.001	0.030	−0.002	−0.070
BLACK	0.007	0.280	0.004	0.180
OTHER RACE	**−0.146**	−3.130	**−0.139**	−2.950
DUAL ELLIGIBILITY	**0.099**	4.270	**0.093**	3.930
MEDIGAP	**0.165**	9.800	**0.154**	8.760
RURAL	**0.035**	2.440	**0.036**	2.470
VISION PROBLEM	−0.042	−1.410	−0.043	−1.410
HEARING PROBLEM	**−0.060**	−1.970	**−0.068**	−2.190
EDUCATION LEVEL2	−0.032	−1.080	−0.043	−1.420
EDUCATION LEVEL3	−0.003	−0.090	−0.017	−0.530
EDUCATION LEVEL4	−0.003	−0.200	0.001	0.090
EDUCATION LEVEL5	0.009	0.680	0.008	0.560
EXC/GOOD HEALTH	0.027	1.600	0.027	1.570
ADL1TO3	−0.025	−1.430	−0.022	−1.210
ADL4TO5	−0.010	−0.280	−0.008	−0.210
IADLTELE	−0.072	−2.390	**−0.074**	−2.450
IADLBILS	−0.006	−0.210	0.001	0.040
NORTH CENTRAL	−0.012	−0.570	−0.015	−0.730
SOUTH	−0.012	−0.620	−0.018	−0.940
WEST	**−0.113**	−5.330	**−0.125**	−5.660
PUERTO RICO	−0.045	−0.740	−0.064	−1.020
AGE7584	**−0.072**	−5.040	**−0.068**	−4.670
OVER85	**−0.151**	−7.160	**−0.139**	−6.330
INCOME LEVEL2	0.012	0.680	0.008	0.440
INCOME LEVEL3	**0.074**	3.310	**0.071**	3.170
HEART	0.019	1.340	0.015	1.050
STROKE	0.013	0.630	0.016	0.750
CANCER	**0.064**	3.840	**0.061**	3.600
DIABTS	−0.002	−0.100	−0.009	−0.490
EMPHYS	−0.016	−0.800	−0.018	−0.890
MARRY	**0.041**	2.540	**0.041**	2.520
HOUSEHOLD COMP	−0.008	−1.180	−0.008	−1.200
Adjusted R^2	0.174		0.166	
F-statistic	26.770		25.410	
N	4296		4296	
Pr, Test of Overid			0.409	

positive income effects if the income effect on demand for curative services is also positive.

Race and ethnicity appear to have significant effects on flu shot demand. Specifically, black beneficiaries and Hispanics have significantly lower probabilities of receiving a flu shot, ceteris paribus. Corresponding effects on mammography demand, however, are not significant. Our four education dummies are also insignificant in both Tables 3 and 4 although the pattern of point estimates for their coefficients suggests a positive gradient for a continuous education measure. Other demographic variables have no significant effects on flu shot demand although there is weak evidence of a positive age effect. In the case of mammography, age has a strongly negative effective while the dummy for marital status has a significantly positive coefficient.

Relatively few of the results for the health problems and disability variables are significant in any of the models. Beneficiaries with one major disease, cancer, have a greater likelihood of receiving each of the preventive services. Women with a hearing problem have a significantly lower probability of mammography use. Those women with significant (four or more) limitations in activities of daily living (ADLs) are less likely to receive mammography screening. This finding may reflect individuals who can not seek care independently.

Results for location variables are mixed. The rural population receives more of both preventive services than those residing in urban areas. On the other hand, neighborhood effects are not significant at the 0.05 level in either 2SLS model.

In addition to the results just presented, we also estimated our two demand models with the prior use variables excluded. This did not substantially alter our findings. The magnitude of the TSLS coefficient for benefits knowledge increased by about 35% in the flu shot model but was essentially unchanged in the mammography model. Corresponding OLS coefficients increased in magnitude by about 90% in the flu shot model and about 45% in the mammography model. We experimented with using an additional instrument in each of the two demand models consisting of the binary variable associated with the preventive service knowledge question in the other demand model. (This test was restricted to female respondents). For example, in the model for mammograms, the instrumental variables used were general Medicare program knowledge and knowledge of the flu shot benefit. These additional variables yielded little additional predictive value as instruments and resulted in rejection of the test for our exclusion restrictions. This latter finding could be a refection of the fact that a 'taste' for preventive care is common to both services.

We also examined interaction effects of benefits knowledge with prior use, both by adding an interaction term to our models and by estimating separate regressions for those with and without prior use. For flu shot use, OLS estimation of the model with an interaction yielded a positive and significant main effect for benefits knowledge of 0.055 and a significant interaction effect of 0.073. Two-stage estimates, with both the main and interaction knowledge variables endogenous, yielded implausibly large coefficients that were very sensitive to the choice of instruments. In the separate sample regressions, OLS estimation yielded significantly positive benefit knowledge coefficients of 0.111 and 0.068 for those with and without prior flu shot use, respectively. Two-stage estimation yielded a small and insignificantly positive benefits knowledge coefficient for those with no prior use and a very large (0.334) and significant coefficient for those with prior use.

For mammography, OLS estimation of the model with an interaction yielded a positive and significant main effect for benefits knowledge of 0.082 and a moderately significant ($p = 0.078$) interaction effect of 0.053. Two-stage estimates, with both the main and interaction knowledge variables endogenous, yielded large and imprecise coefficient estimates. In the separate sample regressions, OLS estimation yielded very similar positive and significant coefficients of 0.110 and 0.090 for those with and without prior mammography use, respectively. Two-stage estimation yielded significantly positive benefits knowledge coefficients of 0.285 and 0.170 for those with and without prior use, respectively.

Taken together, these various results suggest that the positive benefits knowledge effects on use are larger in magnitude for persons with prior use. It is also true, however, that persons with prior use will tend to have better benefit knowledge. (Mean values of FLUKNOW were 0.852 and 0.631 for persons with and without prior use, respectively. Corresponding means for MAMKNOW were 0.802 and 0.506.) Thus, our results do not necessarily suggest that education efforts should be targeted specifically to those with prior use; we suspect that it is more cost effective to target these efforts to groups that have the lowest average level of benefit knowledge.

Discussion

To place the results just described in a broader context, it is useful to compare them with findings from earlier related studies. First, it is interesting to note that our finding of positive knowledge impacts on demand for services is qualitatively similar to knowledge effects reported by Hsieh and Lin [3] and by Kenkel [2]. Our application differs from these previous works, however, in that knowledge in our study basically measures awareness that the out-of-pocket price of a preventive service is zero; thus a positive knowledge effect is clearly to be expected and is logically consistent with rational consumer behavior. We also note that our main result is robust to estimation technique (OLS vs. TSLS), and to the inclusion or exclusion of a measure of prior service utilization as an explanatory variable. Inclusion of this variable does, however, diminish the magnitude of the knowledge effect.

Our study differed from Hsieh and Lin by including education variables in the structural demand function rather than simply using them as instruments for our knowledge variables. In both our OLS and instrumental variables results, however, we find little evidence of a general education effect on demand. (We do note that the coefficients for the education dummies in the mammography regressions suggest the presence of a positive education gradient in demand.) In alternative empirical models, we tried repeating the approach of Kenkel and Hsieh and Lin to include education as instrument in addition to our other knowledge variables. This approach yielded similar results. Thus, our results provide support to Hsieh and Lin's presumption that when more focused measures of knowledge are available, measures of general educational attainment can be used as instruments and excluded from the structural demand function.

Our results for flu shot demand can also be compared directly to the recent findings by Mullahy [5]. His analysis, based on 1991 National Health Interview Survey (NHIS), indicates that self-assessed health status has a strong negative relationship to flu shot demand while years of schooling is a strongly positive predictor. While these results contrast to our own findings, Mullahy also confirms our result of a significantly lower flu shot probability for African Americans. There are important differences in model specification, which could easily explain the differences in results. These include our inclusion of income as a demand factor and the absence from the NHIS data set of many of the variables relating to health and disability status used in our analysis.

The policy implications of our study are significant in a climate where CMS desires elderly beneficiaries to play a greater role in their own health service utilization as well as health plan choice. The results show that knowledge is an important attribute in medical care demand. Few health care empirical studies measure knowledge directly. The rapidly growing consumer choice and information literature provides data on self-reported information sources and health plan choice. With the development of different benefit options for CMS beneficiaries on the horizon, policy evaluations should consider recording measures of benefit knowledge as well as information sources to better understand the value of information dissemination.

An obvious extension of to our analysis would be to examine the impact of Medicare program knowledge on medical expenditures. This analysis could be used to compute the net fiscal impact to Medicare of funds spent on direct consumer education campaigns. Given the fiscal realities of an aging population, a future analysis of the relationship between knowledge, preventive services use, and health care expenditures would be valuable.

Conclusions

Economists commonly assume that consumers make rational choices with perfect information. In health care, however, most consumers understand relatively little about the consequences of their purchases or even the complex arrangements under which these purchases are made. In this study we specifically focus on consumer knowledge of insurance benefits as it affects demand for preventive health services. We find that even controlling for prior use (which could be viewed in part as a proxy for experiential learning), knowledge of the insurance benefit is one of the strongest factors affecting the use of influenza vaccination in the non-institutionalized elderly population and mammography screening within the female non-institutionalized elderly. Our findings of positive income and insurance effects on demand (in the context of full coverage for these preventive services), as well as race/ethnicity differences (especially for flu shots) suggest that complementarities exist between demand for curative and preventive services and that policies to reduce social disparities in the receipt of curative care among Medicare enrollees will also reduce disparities in receipt of preventive services.

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Notes

a. This project intended to provide CMS with an understanding of the needs of Medicare beneficiaries with respect to two basic questions: what information do beneficiaries want and need from CMS; and how can CMS best get this information to beneficiaries. This project was conducted by the Barents Group LLC, the Project HOPE Center for Health Affairs, and Westat, Inc.

Appendix A MCBS KNOWLEDGE QUESTIONS

The five questions below are the items from the MCBS survey that we used to measure consumer knowledge. The first two items pertain to flu shot and mammography coverage. The fourth and fifth items, which pertain to general knowledge about Medicare program rules, were used as instruments. All items were coded as binary 0–1 variables with 1 signifying the correct answer and 0 signifying all other answers.

1. Medicare pays for flu shots. [PROBE: Do you think this is true or false, or are you not sure?]

TRUE. 1
FALSE 2
NOT SURE. 3
REFUSED . . . . −7

IF SP IS FEMALE, ASK 2. ELSE, SKIP TO 3

2. Medicare pays for a mammogram every two years. [A mammogram is an X-ray to check for breast cancer.] [PROBE: Do you think this is true or false, or are you not sure?]

TRUE. 1
FALSE 2
NOT SURE. 3
REFUSED . . . . −7

3. Medicare pays for an annual physical examination. [PROBE: Do you think this is true or false, or are you not sure?]

TRUE. 1
FALSE 2
NOT SURE. 3
REFUSED . . . . −7

4. A doctor who accepts assignment cannot charge more than Medicare allows for covered services. [PROBE: Do you think this is true or false, or are you not sure?]

TRUE. 1
FALSE 2
NOT SURE. 3
REFUSED . . . . −7

5. If you do not agree with a decision Medicare makes on a claim from a doctor or hospital, such as whether it will cover the service or how much it will pay, you can appeal the decision. [PROBE: Do you think this is true or false, or are you not sure?]

TRUE. 1
FALSE 2
NOT SURE. 3
REFUSED . . . . −7

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