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INFORMATION AND THE DEMAND FOR SUPPLEMENTAL MEDICARE INSURANCE

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ABSTRACT

While the critical role of imperfect information has become axiomatic in explaining health care market failure, the theory is backed by little empirical evidence. In this paper we use a unique panel data set with explicit measures of information and an educational intervention to investigate the role of imperfect information about health insurance benefits on the demand for supplemental Medicare insurance. We estimate a structural discrete choice model of the demand for supplemental Medicare insurance that allows imperfect information to affect both the mean and the variance of the expected benefits distribution. The empirical specification is a structural panel multinomial probit with an unrestricted variance-covariance, including heteroskedasticity and random effects to control for unobserved heterogeneity. The model is computationally complex and is estimated by simulated maximum likelihood.

The empirical results indicate that imperfect information affects the demand for supplemental Medicare insurance by increasing the variance of the expected benefits distribution rather than by systematically shifting the mean of the distribution. We find that the increase in variance due to imperfect information increases the probability of choosing *not* to purchase supplemental insurance by about 23%. We also found that controlling for unobserved heterogeneity is important. The goodness of fit increased by about 25% and the precision of the estimated effect of information on the variance of the expected benefits distribution improved dramatically.

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I. INTRODUCTION

Much of the theoretical literature on health care since Arrow (1963) has pointed to imperfect information as a central explanation of market failures. However, while the critical role of information has become axiomatic, the theory is backed by little empirical evidence and there are few estimates of the magnitude of the impact of information on decision making. Moreover, while all second best policies are based on knowing the distribution of information, few information distributions have ever been estimated. This paucity of empirical work is primarily due to the lack of explicit measures of the state of information in existing data sets. In this paper we use a unique panel data set with explicit measures of information and an educational intervention to investigate the role of imperfect information about health insurance benefits on the demand for supplemental Medicare insurance.

Medicare is an entitlement program that provides limited medical care insurance coverage to individuals aged 65 and over. It is the major source of health insurance for older individuals in the U.S. Because of Medicare's limitations, individuals still face substantial out-of-pocket financial risk from medical care costs associated with ill-health (Rankin, 1988; Monheit and Schur, 1989). As a result, about 80 percent of individuals aged 65 and over own supplemental policies that help fill the gaps in Medicare (Monheit and Schur, 1989). The demand for supplemental insurance is expected to greatly expand because of the rapidly growing number older individuals with large health care demands and the possible future reductions in Medicare benefits as a result of health care reform.

Recent policy concern has focused on the fact that individuals may not be sufficiently knowledgeable about supplemental Medicare insurance benefits to make rational choices (New York Times, 1991). McCall, Rice and Sangl (1986) reported that Medicare beneficiaries do not have high levels of knowledge of their benefits and Rice, McCall and Boismier (1991) concluded that better informed beneficiaries made more "effective" choices. In order to improve information, Congress passed legislation standardizing Medigap policy benefit packages in 1992.

However, little is known about the effects of imperfect information in health care markets in general, let alone in the supplemental Medicare market. Almost all of the studies in this area have used indirect proxy measures of information. Moreover, despite Stigler's (1961) observation that uncertain information is captured in the *dispersion* of prices, most previous empirical work has focused on the impact of proxy information measures on the *mean level* of prices.[1] For instance, the largest body of work investigated the extent to which advertising influenced the mean of health care prices (e.g. Benham, 1972; Cady, 1976; Feldman and Begun, 1978; Kwoka, 1984). Others have investigated the effect of provider and population densities as proxies for information on mean physician and hospitals prices (e.g. Pauly and Satterthwaite, 1981; Frech and Wooley,1989). The few studies that have used direct measures of information include Kenkel (1989, 1990), who studied the direct effect of information on health-related behaviors (e.g. smoking, drinking) and medical care utilization, and Davidson el. al (1992), who investigated the direct effect of information on the demand for supplemental Medicare insurance.

Restricting empirical models to allow information to affect decisions only by changing the mean of the distribution of benefits (or costs) may seriously bias estimates of the impact of imperfect information on decision making. In this paper, we specify and estimate a structural model that allows information to shift both the mean and the variance of the expected benefits distribution.

More specifically, we estimate a structural discrete choice model of the demand for supplemental Medicare insurance. Consumers have three options: (i) not to supplement and rely only on Medicare for health insurance, (ii) purchase supplemental coverage from a health maintenance organization (HMO), and (iii) purchase supplemental fee-for-service coverage or so called Medigap policies (FFS). The utility function conditional on choosing a particular alternative contains the expected benefits from purchasing the particular supplemental insurance package and

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1 A notable exception is Gaynor and Polachek (1992) who attempted to decompose the variance in the distribution of physician fees into uncertain information and other sources. However, due to lack of data on information, they were forced to identify the information effects through functional form assumptions.

the value of consumption after having paid for the insurance. The insurance premium enters the model by reducing the value of consumption after purchasing the insurance. Information enters the model through the valuation of the benefits. The individual's valuation of the benefit is specified to be the true benefit plus a random error reflecting variation in tastes and information. The information portion of the error is generated from a subjective information probability distribution. More diffuse information implies a greater variance of the expected benefits distribution and increases the probability that an individual makes mistakes. Consumers compare the three options and choose the one that appears to offer the highest utility. The probability of choosing an alternative is the demand for that alternative. We test whether information affects demand function by altering both the mean and the variance of the expected benefits distribution.

The discrete choice model requires functional forms for the conditional utility function and the stochastic distributions. We specify a flexible conditional utility function that places no restrictions on the marginal rate of substitution of insurance benefits for non-insurance consumption and a stochastic model that places no restrictions on correlations across time and alternatives (other than those necessary for identification). The error structure is allowed to be heteroskedastic to test whether individuals with less knowledge about Medicare benefits draw from distributions with larger variances. Moreover, we take advantage of the panel structure to control for unobserved heterogeneity. In summary, we estimate a panel multinomial probit with an unrestricted variance-covariance, including heteroskedasticity and random effects.

Most studies of discrete choice models have chosen multinomial logit (MNL) over multinomial probit (MNP) models because MNL are computationally very easy to estimate. However, MNL models impose severe restrictions on the covariance structure, which makes them unsuitable for our application since we want to model information in the error structure as well individual correlation over time. The disadvantage of MNP is their computational complexity. We overcome this complexity by using a simulated maximum likelihood estimator to keep the model computationally feasible.

II. THE ROLE OF INFORMATION

Before specifying the empirical model, we illustrate how uncertain information can affect the demand for a health insurance package with a simple example. The problem is framed as a discrete choice problem in which consumers are offered an insurance package with a fixed set of benefits for a certain price. The analysis obviously applies to situations other than health insurance in which consumers face discrete choices.[2]

Consider individuals purchasing an insurance policy at price (P) that provides a single standard benefit package. While everyone receives the same benefit package, the value of the benefit differs across individuals due to factors such as risk preferences, health status, and expected health care utilization. Individual i's value of the benefit in monetary units is given by B_i and is distributed in the population according the density function $f(B)$.

Under perfect information, an individual purchases insurance if $B_i > P$, implying that the aggregate demand function is $Y = \int_P^\infty f(t)dt$. This demand function is presented in figure 1, with those choosing insurance given by the shaded area under the curve to the right of P.

However, individuals rarely know the true benefit package, but rather have misperceptions generated from the ways in which information diffuses throughout a population. Under uncertain information, individuals believe the value of their insurance expected benefit to be $\hat{B}_i = B_i + \mu_i$, where μ_i is a random draw from a subjective information probability density function $g(\mu)$. We assume that μ_i is uncorrelated with B_i because values of true benefits are deterministic (even though they vary across the population). An individual now purchases insurance if $\hat{B}_i > P$, implying that the aggregate function is $Y = \int_P^\infty h(t)dt$ where $h(\hat{B})$ is the density function of $\hat{B}_i$.

Uncertain information can affect the demand curve in two different ways: a) by shifting the mean of the expected benefit distribution and b) by changing the dispersion (or variance). If the mean of $g(\bullet)$ is zero then the information distribution is centered at the mean of the true expected benefit distribution. In this case, all consumers may misestimate their expected benefit, but there

2 Rosen and Taubman (1979) developed a similar model to examine the role of information in explaining unproductive consumption.

is no overall systematic bias in the population as a whole. However, there is no reason to believe *ex ante* that the mean of μ_i is zero. If the mean is positive, demand will be larger under uncertain information, and, if the mean is negative, demand will be smaller.

The effect of an increase in dispersion depends on whether the price cuts the true benefit distribution is to the left or the right of the mode. The effect of a mean-preserving increase in dispersion is demonstrated in figures IIa and IIb, where h(•), the distribution of perceived benefits ($\hat{B}_i$), is overlaid on f(•), the distribution of true expected benefits B_i, under the assumption that the mean of μ_i is zero. In figure IIa, where price cuts the distribution to the left of the mode, the mean-preserving increase in dispersion shifts mass from the right of price to the left of price, implying a reduction in demand. In figure IIb, where price cuts the distribution to the right of the mode, the mean-preserving increase in dispersion shifts mass from the left of price to the right of price, implying an increase in demand. Thus the probability of choosing an alternative changes with information even if incomplete information does not change the mean of perceived benefits.

As a consequence, an empirical model that does not allow information to affect decisions through both the mean and the variance of the perceived benefits distribution may seriously mis-estimate the impact of information on demand. Moreover, the direction of the bias cannot *a priori* be bounded. Also, a structural interpretation of a statistical model that does not permit for the variance effect, such as the MNL used by Davidson et al. (1992), may mistakenly conclude that information changes the mean level of perceived benefits, i.e. that uninformed individuals systematically over- or underestimate benefits. In the remainder of the paper, we set up and estimate a model that allows information to affect both the mean and the variance of expected benefits.

III. A MODEL OF THE DEMAND FOR SUPPLEMENTAL INSURANCE

In this section we integrate uncertain information into a utility maximizing model of the demand for health insurance supplementing Medicare and derive an empirical specification. We first present the underlying behavioral model, which characterizes the problem as a choice among discrete alternatives. Each alternative has a benefit and a price associated with it. Consumers choose the alternative perceived to provide the highest utility. Converting the behavioral framework into an empirically estimable model requires specification of a functional form for the conditional utility functions and a stochastic model.

Behavioral Assumptions

The basic Medicare program provides a limited amount of insurance coverage for health care services obtained from any provider in the private fee-for-service (FFS) market to individuals age 65 and over. Beneficiaries of this program can supplement Medicare's basic coverage by two mechanisms: either by purchasing private insurance designed to fill some of the gaps left by the federal program ('Medigap' policies), thereby remaining in the FFS market and preserving their choice of provider, or by enrolling in health maintenance organizations (HMOs), thereby leaving the FFS market and agreeing to use only those providers affiliated with the HMO, and in return receiving broader coverage at little additional out-of-pocket cost. Both of these choices basically fill in the gaps left by Medicare's limited coverage. In sum, consumers face a choice of: (1) not purchasing supplement insurance (i.e. Medicare only), (2) purchasing an HMO supplement or (3) purchasing FFS Medigap policies. The cost of a FFS or HMO supplement is reduced consumption of other goods and services.

Let the expected utility for individual i conditional on choosing alternative j in period t be $U_{ijt} = U(\hat{B}_{ijt}, C_{ijt})$ where C_{ijt} is aggregate consumption net of insurance and $j = m, f, h$ which refer to Medicare only, FFS supplement and HMO supplement, respectively. The budget constraint is $Y_{it} = C_{ijt} + P_{jt}$, where P_{jt} is the price of alternative j in period t. Substituting the budget constraint into the conditional utility function yields

$$U_{ijt} = U(\hat{B}_{ijt}, Y_{it} - P_{jt}) \tag{1}$$

The Medicare alternative carries a price of zero so that consumption equals income under that alternative.

The unconditional utility maximization problem is:

$$U^*_{ijt} = max[U_{imt}, U_{ift}, U_{iht}] \tag{2}$$

The solution to the optimization problem in (2) gives the alternative chosen and, when there are random terms in the utility function, the probability the alternative is chosen which is interpreted as the individual demand function. Summing these probabilities over the population gives the aggregate demand function. Indirect utility functions for welfare analysis can be derived from these demand functions (McFadden, 1981; Small and Rosen, 1981).

The Conditional Utility Function

Functional Form: In order to derive an estimable demand function, we need to specify a functional form for the conditional utility function in (1). Consider a function that is linear in parameters:

$$U_{ijt} = \hat{B}_{jt} + \alpha C_{jt} = \hat{B}_{jt} + \alpha\left(Y_{it} - P_{jt}\right) \tag{3}$$

where α is the marginal utility of consumption and $\hat{B}_{ijt}$ is interpreted as the utility from benefit package j. However, a linear utility function imposes a constant marginal rate of substitution between insurance benefits and consumption. In this case, income cannot affect the insurance decision. For example, consider choosing between FFS and Medicare only. FFS is chosen if:

$$U_{ift} - U_{imt} = \hat{B}_{ift} - \hat{B}_{imt} + \alpha P_{mt} > 0 \qquad (4)$$

In other words, FFS is chosen over Medicare only if the marginal utility of the gain in benefits is larger than the marginal utility of foregone consumption. With a constant marginal rate of substitution imposed by the linear functional form, income differences out of the purchase rule.

Intuitively, increases in income only affect conditional utility through consumption, since only P can be spent on insurance. Under the assumption of constant marginal rate of substitution, income does not affect the choice because consumption is always substituted at the same rate for benefits regardless level of consumption. Therefore, the comparison of marginal utility of benefits, $\hat{B}_{ift} - \hat{B}_{imt}$, to marginal utility of foregone consumption αP_{mt} in the decision rule specified in (4) is the same for all levels of income. However, if there is a diminishing marginal utility of consumption and therefore a diminishing marginal rate of substitution, then marginal utility of forgone consumption falls as consumption and therefore income rises. We allow for this possibility by allowing α to depend on income (Y).

The Utility of Expected Benefits: A second specification issue concerns the fact that there are no direct measures of utility of benefits ($\hat{B}_{ijt}$). Instead we parameterize it to be a function of individual characteristics with the coefficients allowed to differ by alternatives. The utility of expected benefits from alternative j is:

$$\hat{B}_{ijt} = \beta_{0j} + \sum_{k=1}^{K} \beta_{kj} X_{ikt} + \lambda_j \mu_{it} + \varepsilon_{ijt} \qquad (5)$$

where X is a vector of individual characteristics that affect the individual's value of the benefit package (e.g. health status, whether they have a regular physician, education, marital status). The alternative specific intercept picks up the overall mean in the utility of expected benefits and is augmented for each individual based on observed and unobserved individual characteristics. The coefficients on the individual characteristics (X) are allowed to differ by alternative because, for example, having a regular physician may make FFS supplemental insurance more valuable than HMO supplemental insurance.

Uncertain information is introduced into the model through the random component in (5). The random component in (5) consists of two additive factors which are assumed to be uncorrelated with one another. The second random term, (ε_{ijt}), reflects "true" factors (e.g. preferences) unobserved to the econometrician, whereas the first term ($\lambda_j \mu_{it}$) measures the divergence of the utility of an individual's belief about expected benefits from the utility of the true expected benefits. Uncertain information is introduced through the μ_{it} term. If the individual has perfect information, then the value of μ_{ijt} is zero. How uncertain information affects the demand, depends on the distribution of μ_{ij}. The coefficient λ_j measures the alternative specific utility of the information.

Identification: Not all of the parameters in the conditional utility functions are identified. Since the demand function for alternative j is the probability that the utility from j is greater than the utility from all other alternatives, the demand function is based on differences in the conditional utility functions. Therefore, as illustrated above in the case of income, terms that do not vary across alternatives are differenced out of the model. Therefore, either the value of the variable or the coefficient must vary across alternatives for the complete term not to be differenced out of the demand function. Parameters that are constant across alternatives are identified if the value of the variable differs across alternatives. For example, the marginal utility of consumption α is the same across alternatives and is identified by the fact that the price varies by alternative.

For variables that have the same value across alternatives (e.g. age, education, marital status), the coefficient must vary across alternatives in order not to be differenced out of the demand function. Because only differences in the coefficients that vary across alternatives can be identified, we normalize the coefficients in the Medicare utility of expected benefit function to zero and interpret the coefficients in the other alternatives relative to Medicare. In this case, the marginal utility of FFS and HMO supplements are:

$$U_{ijt} - U_{imt} = \beta_{0j} + \sum_{k=1}^{K} \beta_{kj} X_{ikt} - \alpha P_{jt} + \lambda_j \mu_{it} + \varepsilon_{ijt} - \varepsilon_{imt}, j = f, m \qquad (6)$$

The intercept and the coefficients on the X's are interpreted in terms of affecting the *marginal* utility of the expected benefits from insurance supplementing Medicare.

The Demand Functions

The demand function for alternative j in period t is the probability individual i chooses j, i.e. the probability that the perceived utility from j is greater than the utility obtained from any other alternative. In order to derive the demand functions we need to specify the distributions of ε_{ijt} and μ_{it}. We assume that $\varepsilon_i \sim N(0,\Omega)$, where Ω is a 6x6 matrix (3 choices, 2 periods), and that the conditional subjective probability distribution is $\mu_{it} | I \sim N(\mu(I),\kappa(I))$, where I is a measure of the individual's knowledge of insurance benefits.

As in the case of the utility function, not all of the variance parameters can be identified. Indeed, identification of the variance parameters is a difficult topic, first discussed by Daganzo (1979) and more recently by Bunch (1991). Estimatibility requires two normalization's on the variance-covariance matrix. First, because choice probabilities depend only on differences in utility and therefore on the distribution of differences in the error, we can reduce the dimensionality of Ω by 1 for each period and thereby implicitly normalize one choice specific random component to be zero. A second normalization is necessary because the probability $\Phi(V,\Omega)$ is the same as the probability $\Phi(kV, k^2\Omega)$. Therefore, we normalize the trace of the covariance (sub-)matrix to equal $\pi^2/2$ for each period, which makes the size of the parameters in the mean function comparable to the multinomial logit estimates[3]. These standard normalizations are discussed in Bunch (1991).

We introduce two additional aspects to the variance covariance matrix. First, because, we observe individuals at two points in time, we control for unobserved heterogeneity with an individual random effect than picks up unobserved correlation over time, i.e. $cov(\varepsilon_{ijt}\ \varepsilon_{ilt+1}) \neq 0$. This correlation over time captures the persistence in insurance choices over time that may be due to unobserved preferences. This persistence has been found to be important in other studies of insurance demand (e.g. Neipp and Zeckhauser, 1985 and Ellis, 1985 and 1989). Second, we can introduce additional variance effects that differ across individuals and choices according to other covariates without an identification problem. Therefore, to estimate the effect of information on the dispersion of the value of expected benefits, we add the term $\kappa(I)=c^2*(I)$ to the first diagonal element.

In summary, our specification for the variance-covariance matrix is:

$$\Omega + \kappa(I_t, I_{t+1}) = \begin{matrix} \omega_{11} + c^2 I_t & \omega_{12} & 0 & \omega_{14} & \omega_{15} & 0 \\ \omega_{21} & \omega_{22} & 0 & \omega_{24} & \omega_{25} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \omega_{41} & \omega_{42} & 0 & \omega_{44} + c^2 I_{t+1} & \omega_{45} & 0 \\ \omega_{51} & \omega_{52} & 0 & \omega_{54} & \omega_{55} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{matrix} \qquad (7)$$

where $\omega_{11} + \omega_{22} = \omega_{44} + \omega_{55} = \pi^2/2$. For comparison, note that the covariance matrix of the MNL can be written as a diagonal matrix with elements $\pi^2/6$.

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[3] The variance of the extreme value distribution underlying the random utility interpretation of the multinomial logit is $\pi^2/6$.

IV. DATA

Source and Sample

The data used in this study were collected from a sample of 332 Medicare beneficiaries who attended one of 75 educational workshop held between October 1986 and May 1987 about their insurance coverage options, specifically Medicare itself, private supplementary Medigap policies and Medicate HMOs. These workshops were being offered as part of a HCFA-sponsored research project (Sofaer et. al, 1990). Individuals included in the analysis were 64 years or older, and did not have dual Medicare/Medicaid coverage or both HMO and private supplementary policies. The workshop participants were surveyed before the workshop and approximately one year later about their knowledge of Medicare benefits, perceived health status, socio-economic characteristics, and insurance coverage choices. The data form a two-year balanced panel with the educational workshop intervention occurring in-between. However, because our sample only contains workshop participants and not a random sample of the Medicare population, the generalizability of the findings for policy analysis may be limited. More details on the sample and the variables can be found in Sofaer et. al (1990) and Davidson et. al (1992).

Dependent Variable

The dependent variable is the choice of supplemental Medicare insurance, FFS, HMO or none. The distribution of the choices before and after the educational intervention are displayed in Table 1. Before the intervention, approximately 90% of individuals supplemented Medicare, with two-thirds choosing FFS and one-third choosing HMO. After the intervention, the number of individuals choosing not to supplement fell by about 40%, the number choosing HMOs grew by about a third, and the number choosing FFS fell slightly.

Table 1: Supplemental Insurance Choices

Choice	Year 1		Year 2	
	Frequency	Percentage	Frequency	Percentage
HMO Supplement	85	25.6%	110	33.2%
FFS Supplement	214	64.5%	202	60.8%
Medicare Only	33	9.9%	20	6.0%
Total	332	100.0%	332	100.0%

The choice-transition probability matrix is displayed in Table 2. Despite the education intervention in-between years 1 and 2, the large number of observations on the diagonal indicates the strong persistence of choices over time. The largest number of movers after the educational workshop were those that had only Medicare in year 1. Of those, about half chose to supplement after the intervention splitting equally between HMO and FFS. The next largest group of movers where those that had FFS supplemental insurance before the workshop. Of those, about 15% switched, almost all of which chose HMO. Finally, those that had HMO coverage seemed not to switch at all. Indeed, only about 5% switched to private insurance and none dropped all supplemental coverage.

Table 2: Insurance Choice Transition Probabilities Conditional on Year 1 Choice and (Cell Size)

YEAR 1	YEAR 2: HMO	FFS	Medicare	Total
HMO	0.95 (81)	0.05 (4)	0.00 (0)	1.00 (85)
FFS	0.10 (22)	0.87 (187)	0.02 (5)	1.00 (214)
Medicare	0.21 (7)	0.33 (11)	0.45 (15)	1.00 (33)
Total	0.33 (110)	0.61 (202)	0.06 (20)	1.00 (332)

Independent Variables

Descriptive statistics of the independent variables are given in Table 3. Most of the demographic independent variables are self-explanatory — age, sex, white, education and married. Regular doctor is an indicator as to whether the individual had a regular physician over the last 5 years. Income is measured in hundreds of dollars. Rich is an indicator as to whether the individual is in the top quarter of the US income distribution. Rich is included in the model as an interaction with the insurance premium to test whether the price elasticity declines with income. These variables do not chance over time. The remaining independent variables (Medicare benefits knowledge, insurance premium, and health status) are described in more detail below

Table 3: Descriptive Statistics of Independent Variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Medicare Knowledge Index (Year 1)	2.79	7.45	0	5
Medicare Knowledge Index (year 2)	3.55	1.26	0	5
Health Status Index	8.27	2.26	3	12
Have Regular Doctor (= 1)	0.39	0.49	0	1
Age	71.31	5.72	64	90
Gender(Female = 1)	0.36	0.48	0	1
Race (White = 1)	0.92	0.28	0	1
Education (Yrs of Schooling)	13.92	3.02	8	20
Married (= 1)	0.49	0.50	0	1
HMO Premium (year 1)	2.70	1.16	0.52	3.31
HMO Premium (year 2)	2.73	0.90	1.04	3.20
FFS Premium (year 1)	5.65	1.80	2.27	6.60
FFS Premium (year 2)	4.45	1.29	2.02	5.13
Income (00's)	249.52	196.65	50	735
Rich (= 1 if in Top 25% of US)	0.47	0.50	0	1

Information. Information is measured by an index of Medicare benefits knowledge. The Medicare benefits knowledge index is constructed based on respondents' answers to 5 true-false questions about Medicare coverage (see Table 4). The same questions were administered before the educational intervention as part of the year 1 questionnaire and after the intervention as part of the year 2 questionnaire. The 5 individual knowledge items at each wave were combined into an aggregate scale to measure health insurance knowledge. The knowledge scale is simply the sum of individual correct responses. Allowable scores for the Medicare scale range from 0-5.[4]

Table 4: Medicare Knowledge True-False Questions
1. Except for a deductible on the 1st day, Medicare pays all hospital costs for up to 60 days?
2. The costs of eyeglasses are covered by Medicare?
3. Medicare does not cover the cost of prescription drugs you buy at the pharmacy?
4. If I need someone to help me out at home because I can't get around as well as I used to, Medicare will pay the costs?
5. If my doctor accepts assignment, s/he can't charge me more than Medicare allows?

One of the major changes between the first and second rounds was a dramatic improvement in Medicare benefits knowledge. The distribution of correct answers to the Medicare knowledge questions is presented in Table 5. The mean number correct in year 1 is 2.79 out of 5 which is close to the random response mean, 2.5. In year 2 the mean number of correct increases to 3.55. The increase in the number correct is reflected by the shift in mass from the lower tail to the upper tail of the distribution.

4 The construct validity of these 'Likert-type' summated scales was analyzed in three steps to confirm that the items could appropriately be combined. First, correlations among the 5 items were factor analyzed to test the appropriateness of constructing a single summary measure of beneficiary knowledge. Second, the reliability (or item convergent validity) of the 5-item summary scale was estimated as a measure of internal consistency. Third, the concurrent validity of the 5-item scale was tested by evaluating its relationship with selected measures available in the data set See Davidson et al. (1992) for the results of these analyses.

Table 5: Distribution of Medicare Knowledge

# Questions Answered Correctly	Year 1		Year 2	
	Frequency	Percentage	Frequency	Percentage
0	33	9.94%	13	3.92%
1	36	10.84%	11	3.31%
2	52	15.66%	30	9.04%
3	90	27.11%	84	25.30%
4	89	26.81%	115	34.64%
5	32	9.64%	79	23.80&
Total	332	100.00&	332	100.00%

Another consequences of the educational workshop was a narrowing of the information distribution in year 2. The individuals who entered the educational workshop with the least knowledge were the ones who had the largest increase in test scores in year 2. The second column of Table 6 reports the mean change in the knowledge scores conditional on year 1 knowledge. Those whose scored two or less on the year 1 test dramatically increased their number of correct responses. Those who entered the program knowledgeable about Medicare did not in general increase their knowledge, probably because there was little room for improvement for the knowledgeable group. The fact that the greater information gain was among the uninformed led to a narrowing of the dispersion. This is reflected the last column in table 6 which reports the mean number of correct questions in year 2 conditional on year 1 performance.

Table 6: Year 2 Knowledge Conditional on Year 1

# Questions Correct Year 1	Mean Δ in # Correct Year 2	Mean # Correct Year 2
0	2.79	2.79
1	2.28	3.28
2	1.35	3.35
3	0.74	3.74
4	- 0.38	3.62
5	- 0.78	4.22
Average (2.79)	0.76	3.55

Finally, we note that improvements in information are somewhat correlated with switching patterns between year 1 and year 2. Table 7 reports the mean change in Medicare knowledge for each cell in the insurance transition matrix. The last column presents the gain in knowledge conditional on year 1 choice. The largest gainers in information were those who had Medicare in year 1; an increase of 1.27. These were also the individuals most likely to change their insurance coverage in the second year. Of those who had no Medicare supplement in year 1, about half chose to supplement in year 2 and this group of supplementers had larger gains in knowledge than those who chose to remain with Medicare. Among those with FFS in year 1, some individuals switched to HMO and a few dropped all supplementation choosing Medicare only. Those that switched from FFS to Medicare experienced a reduction in of information of -.2 compared to a gain in information of about .6 to .7 for the those that remained with FFS or switched to HMO.

Table 7: Mean Information Change and (cell size) by Insurance Choice Transition

	YEAR 2			
YEAR 1	HMO	FFS	Medicare	Total
HMO	0.83 (81)	0.75 (4)	— (0)	0.82 (85)
FFS	0.59 (22)	0.68 (187)	- 0.2 (5)	0.65 (214)
Medicare	2.00 (7)	1.18 (11)	1.00 (15)	1.27 (33)
Total	0.85 (110)	0.71 (202)	0.70 (20)	0.75 (332)

Preferences and Secular Trends. The main mechanism through which the educational intervention affects our model is through the change in Medicare knowledge. However, the FFS and HMO intercepts are also allowed to be different between periods one and two to account for other possible influences of the educational intervention on insurance choice such as shifts in preferences as well as any other secular trends. The difference is parameterized by including a year 2 dummy variable in both the expected marginal benefits of HMO and expected marginal benefits of FFS equations.

Insurance Premiums. The price of supplemental insurance is measured by the premiums. Average FFS and HMO premiums were constructed off respondents' reports of annual premium expenditures. The averages were constructed for separately for first and second round and based on whether an employer subsidized the purchase of supplemental insurance. Employer subsidies reduced the cost of insurance by more than half. The premiums are reported in hundreds of dollars and the FFS premium is about twice as large as the HMO premium.

Health Status. The measurement of health status is an attempt to assess enrollees' relative health risks that may influence demand for supplemental insurance. A direct measure of health status is available in the data set: perceived health status. Three different questionnaire items for health status were asked at baseline and from them, an aggregate perceived health status scale was constructed. Perceived health status is the sum of scores on the three items asking the respondent to rate his or her present health status, level of concern about health during the past 3 months, and amount of pain experienced during the past 3 months. Each of these 3 items is scored on a 4-point scale, with smaller numbers representing poorer health, more concern or more pain, and larger numbers representing better health, less concern or less pain. Combining these 3 items produces a scale encompassing 3 distinct and relevant dimensions which represent the domain of interest: a health status measure which reflects the relative risk of health service use by enrollees. The construct validity of the aggregate health measure was assessed in two steps.[5]

[5] First, the reliability (or item convergent validity) of the 3-item summary scale was estimated as a measure of internal consistency. Then, concurrent validity was tested by evaluating the relationship of the scale with selected measures available in the data set.

V. ESTIMATION AND RESULTS

Estimation Method

Until recently, there have been few applications using multinomial probit models because of the computational difficulties caused by high dimensional integration. McFadden (1989) suggested the method of simulated moments to circumvent this problem and Hajivassiliou (1992) provides a recent review of this research. We estimate this model using simulated maximum likelihood (Lerman and Manski, 1981, Diggle and Gratton, 1984, Boersch-Supan and Hajivassiliou, 1993, Lee, 1992), which allows us to perform specification tests and final estimation on a fast personal computer using a program written in Gauss.[6]

The standard maximum likelihood method would try to maximize the response probabilities (i.e. the likelihood that an individual chooses the observed sequence of insurance alternatives) as a function of parameters θ. Because it is very difficult to evaluate the response probability $f(\theta)$ and even standard numerical integration only provides an approximation of the "true" $f(\theta)$, the simulated maximum likelihood replaces it by an estimated probability $\phi(\theta)$. This estimated probability is generated by averaging over a number of simulated responses (*draws*). The simulated maximum likelihood estimator maximizes:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ln \phi(\theta),$$

where N is the number of individuals. Because of the nonlinearity of the logarithm and the variance of the estimated response probability, simulated maximum likelihood estimates for a fixed number of draws are not unbiased. However, we consider simulated maximum likelihood estimators as a sequence of functions that converge to the true maximum likelihood estimator as the number of draws increases. We increased draws for the final results until doubling the number

6 The advantage of the simulated methods grows exponentially with the number of dimensions. For example, while numerical integration is slightly faster than the simulation routine with 1000 draws in two dimensions, numerical integration takes already 10 times longer than simulation integration in three dimensions.

of draws did not change parameter and variance estimates by more than 1/100. This provides sufficient precision for the purposes of this paper and we are therefore not concerned with the asymptotic theory of the simulation variance or bias, discussed in Lee (1992).

We used the GHK simulation algorithm, described in Hajivassiliou, McFadden, and Ruud (1992), to integrate multivariate densities. However, while Boersch-Supan and Hajivassiliou (1993) found that 20 draws were sufficient to produce a negligible bias in their Monte Carlo example, there was a large variance and a substantial bias for 20 draws in our application. This is to some extent due to the covariance matrix, which is "far" from being diagonal, and the additional complexities that a real application entails. However, 20 draws provided good starting values, 100 draws provided good point estimates, and 250 draws provided good estimates of standard errors. The MNP results reported in Table 3 are for a final run with 1000 draws.

Specification Sensitivity

We estimated several versions of the model to explore the sensitivity of the specification. We found that several variables were clearly irrelevant in that their coefficients were never significant (in any model) and their exclusion did not influence the other coefficients. As a result we deleted age, race, and gender. Furthermore, we could not reject the hypothesis that the coefficients on health, regular doctor, and the interaction between regular doctor and health were the same in the HMO and FFS expected benefits functions. This was somewhat surprising since we expected that individuals who have a long standing relationship with a physician would prefer FFS to HMO supplement. We therefore constrained these coefficients to be equal for FFS and HMO. However, the intercept, period 2 dummy, marital status, education and the interaction between rich and premium were left unconstrained. These restrictions substantially improved numerical convergence, which is not unexpected given the recent findings that MNP models can be very fragile (Keane, 1992).

We also estimated the model under three different stochastic assumptions in order to assess their restrictiveness: (i) a MNL version that assumed independence across alternatives and time as well restricted uncertain information to enter only through the mean of the marginal utility of expected benefits, (ii) a MNP which included allowed information to affect the variance and an unconstrained covariance within each period (but which ignored the longitudinal design, i.e. $\omega_{14}, \omega_{15,} \omega_{24}, \omega_{25} = 0$), and finally (iii) a model that in addition allowed for serial correlation.

Unfortunately, we did not achieve convergence for the model with the full unconstrained covariance matrix (7) because the matrix became singular during iterations. This was caused by the very large serial correlation as soon as we allowed for correlations between ε across periods. The last two columns in Table 3 correspond to the covariance matrix with $\omega_{14} = \omega_{25}$ (coefficient estimate in the second to last row), identical diagonal elements, and other off-diagonal elements equal to zero. We tried several other specifications with additional parameters (e.g. including parameters for ω_{12}, ω_{15}) and achieved convergence, but none of these other specifications yielded a significant improvement in the log-likelihood.

Turning to Table 8, consider first the differences between cross-sectional and longitudinal models (i.e the models that controlled for unobserved heterogeneity). The logit and probit specifications without the person (first two columns) are quite similar in terms of goodness-of-fit. The difference between the first and second models is that the MNP allows for correlation across alternatives, includes the information effect in the variance, but excludes the information effect on mean. However, the goodness of fit does not change when both the cross-sectional MNP contains both mean and variance information effects since both information effects are insignificant.

Table 8: Multinomial Probit (MNP) Models of The Demand for Supplemental Medicare Insurance

	Multinomial Logit	MNP (No Random Effect)	MNP (Random Effect)	MNP (Random Effect)
mean log likelihood	-.8122	-.8215	-.6348	-.6358
Price Coefficients				
premium	.3000*** (.1175)	-.220** (.089)	-.268** (.120)	-.258** (.122)
premium*rich	.1182** (.0558)	.084** (.040)	.004 (.051)	.008 (.052)
HMO marginal benefits function				
constant	.6691 (1.078)	1.167 (.892)	.780 (1.30)	1.027 (1.415)
year 2 dummy variable (year 2 = 1)	.6901** (.3332)	.713*** (.324)	.529*** (.171)	.589*** (.176)
information index	.0713 (.1045)	-	.098 (.079)	-
health status index	.0105 (.0724)	.003 (.062)	.006 (.085)	.004 (.086)
have regular doctor (doctor = 1)	3.372** (1.549)	2.699** (1.177)	2.920* (1.53)	2.989* (1.567)
regular doctor * health status index	-0.3186* (0.1660)	-.235* (.128)	-.272 (.167)	-.280 (.171)
education (years of schooling)	.0136 (.0587)	-.0123 (.052)	.0097 (.0695)	.0137 (.074)
marital status (married = 1)	0.980*** (0.353)	1.002*** (.336)	.988** (.402)	1.022** (.403)
FFS marginal benefits function				
constant	1.637 (1.287)	2.146** (.976)	1.724 (1.451)	1.938 (1.54)
year 2 dummy variable (year 2 = 1)	.0636 (.3553)	.139 (.286)	-.110 (.228)	-.035 (.230)
education (years of schooling)	.0848 (.0574)	.049 (.043)	.082 (.062)	.0856 (.065)
marital status (married = 1)	.408 (.350)	.422 (.277)	.529 (.352)	.562 (.353)
Variance-Covariance parameters				
person random effect	-	-	2.39*** (.035)	2.38*** (.035)
information effect (5-I)	-	.372 (.310)	.315** (.138)	.400*** (.132)

Note: standard errors in parentheses, significance: *: 10%, **: 5%, ***: 1%.

However, moving to a panel model (the next two columns) that controls for unobserved heterogeneity provides a substantial improvement in goodness-of-fit. In this case, while the information effect in the mean remains insignificant, the information effect in the variance is now significant. Interestingly, the magnitude of the information effect in the variance is the same in the model that ignores unobserved heterogeneity (column 2) as in the models that control for it (columns 3 and 4). Clearly, controlling for unobserved heterogeneity is important for the precision of the estimated effect. Additionally, when we control for unobserved heterogeneity, the interactions between premium and rich and between health and regular doctor lose their significance in the longitudinal models.

Coefficient Estimates

Based on the above discussion we focus our attention on the models in last two columns of Table 3. The coefficient estimates are largely consistent with common expectations. The coefficient on insurance premium is significantly negative indicating that an increase in premiums reduces the demand for insurance. The interaction between premium and rich is positive, but insignificant. The sign indicates that wealthier individuals may be less price sensitive. The next set of coefficients starting with constant (HMO) through married refer to the coefficients in the marginal utility of expected benefits from HMO. The last set of coefficients staring with constant (FFS) refer to the coefficients in the marginal utility of expected benefits from FFS. Since the coefficients on health, regular doctor, and the interaction between regular doctor and health were constrained to be the same for the HMO and FFS alternatives, they are not repeated.

We begin with the coefficients that are common to HMO and FFS. Those individuals who were in good health and had a regular doctor were more likely to purchase insurance. However, health status seemed to have no impact for those without a regular doctor. Individuals with a regular doctor, however, were more likely to purchase insurance and the effect increased as health status worsened.

Turning to the coefficients that differed across HMO and FFS, the period two dummies indicate that, as a result of the educational intervention above and beyond the effect through the information variable, the second period demand for HMO increased over first period but not for FFS. Thus, the workshop appears to have changed "tastes" in favor of HMOs. Finally, an individual's formal education seemed to have no significant impact, but married individuals were much more likely to choose HMO.

The second last row reports the person-specific variance effect. Notice the strong positive and highly significant person-specific effect. This implies that the choices are highly correlated over time through unobserved preferences. This is consistent with the strong persistence effects in insurance demand reported by Neipp and Zeckhauser (1985) and Ellis (1985 and 1989).

The last column reports the effect of information on the variance. This effect is positive and significant. Therefore, poor information increases the variance of the marginal utility of expected benefits. Since the mean information effect is small and not significantly different from zero, we conclude that the main effect of information is through increases in variance. When the restriction of no mean bias is imposed (final column), the variance effects increases by about a quarter.

Information and Price Effects

The estimation results indicate that information affects the choice only though the variance term. Therefore, since the majority of the sample choose to purchase supplemental insurance and the price cuts the distribution to the left of the mode, improvements in information that reduce the variance increase the demand for supplemental insurance. In this section we estimate the magnitude of the information effects and compare them to the magnitude of price effects, based on the model in the last column of Table 8.

Tables 9 and 10 report simulations of the effect of "policy experiments" on the demand for Medicare supplements for an individual with mean sample characteristics. Beginning with Table 4, in a group with the average understanding of Medicare and personal characteristics of our sample, 8.2% would not buy supplementary coverage. With minimal (no) information, this proportion increases to 9.5% (a 15% increase); with maximum information, this proportion decreases to 7.5% (a 21% decrease from the situation with minimal information). Using the results reported in Table, we compare the size of the information effect with reductions in the premiums of supplementary plans. We estimate that improving an individual's information about Medicare benefits from the mean to the maximum level has the same effect on demand as a 25% reduction in the premiums of supplementary health insurance.

Table 9:
The Effect of Changes in Information on Buying No Supplements

	no information	sample mean information	full information
variance effect	9.6%	8.2%	7.4%

Note: predictions for individual with mean sample characteristics.

Table 10:
The Effect of Reducing the Cost of Supplements on Buying No Supplements

actual price	10% reduction	20% reduction	30% reduction	50% reduction
8.2%	7.4%	6.5%	5.8%	4.5%

Note: predictions for individual with mean sample characteristics.

VI. SUMMARY

In this paper we used a unique panel data set with explicit measures of information and an educational intervention to investigate the role of uncertain information about health insurance benefits on the demand for supplemental Medicare insurance. We estimated a structural discrete choice model of the demand for supplemental Medicare insurance that allows imperfect information to affect both the mean and the variance of the expected benefits distribution.

We estimated a model that included a flexible conditional utility function that placed no restrictions on the marginal rate of substitution and a stochastic model that placed few restrictions on correlations across time and alternatives. In particular, the error structure was allowed to be heteroskedastic to test whether individuals with less knowledge about Medicare benefits get their information from distributions with larger variances. Moreover, we took advantage of the panel structure to control for unobserved heterogeneity. In sum, we estimated a structural panel multinomial probit with an unrestricted variance-covariance, including heteroskedasticity and random effects. In order to overcome the computational complexity of this problem we used a simulated maximum likelihood estimator.

The empirical results indicated that imperfect information affects the demand for supplement Medicare insurance by increasing the variance of the expected benefits distribution rather than by systematically shifting the mean of the distribution. Since the majority of people already purchase insurance, an increase in variance due to imperfect information reduces demand. We estimate that if everyone has perfect information, then the proportion of individuals not purchasing insurance would fall by 23% from .096 to .074.

We also found that controlling for unobserved heterogeneity was important. The goodness of fit increased by about 25% and the precision of the estimated effect of information on the variance of the expected benefits distribution increased dramatically. More specifically, while the size of the estimated information effect was approximately the same in the model that controlled for unobserved heterogeneity and the one that did not, the effect was significant only in the model that controlled for unobserved heterogeneity.

References

Arrow, K. (1963) "Uncertainty and the Welfare Economics of Medical Care "*American Economic Review*, 53:941-973.

Berkovec, J. and S. Stern (1991) "Job Exit Behavior of Older Men," *Econometrica*, 59, 189-210.

Boersch-Supan, Axel and Vassilis Hajivassiliou (1993) "Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models," *Journal of Econometrics*, 58(3), 347-368

Benahm, L. (1972) "The Effect of Advertising on the Price of Eyeglasses," *Journal of Law and Economics*, 15: 337-452.

Bunch, D.S. (1991) "Estimability in the Multinomial Probit Model," *Transportation Research*, 25B(1), 1-12.

Cady, J.F. (1976) "An Estimate of the Price Effects of Restrictions on Drug Price Advertising," *Economic Inquiry*, 14: 493-510.

Daganzo, C. (1979) <u>Multinomial Probit</u>, Academic Press, New York

Dansie, B.R. (1985) "Parameter Estimability in the Multinomial Probit Model," *Transportation Research*, 19B, 526-528.

Davidson, B.N., S. Sofaer, and P. Gertler (1992) "Consumer Information and Biased Selection in the Demand for Coverage Supplementing Medicare," *Social Science & Medicine*, 34(9), 1023-1034.

Diggle, P.J. and R. J. Gratton (1984) "Monte Carlo Methods of Inference for Implicit Statistical Models," *Journal of the Royal Statistical Society*, B, 46(2), 193-227.

Ellis, R. (1985) "The Effect of Prior Year Health Expenditures on Health Coverage Plan Choice, in R. Scheffler and L. Rossiter (eds.), <u>Advances in Health Economics and Health Services Research</u> Vol. 6, (Greenwich, CT.; JAI Press)

Ellis, R. (1989) " Employee Choice of Health Insurance" *Review of Economics and Statistics*, pp. 215-223.

Feldman, R. and J. Begun (1978) "The Effects Advertising Restrictions: Lessons From Optometry," *Journal of Human Resources*, Supplement 13: 247-262.

Gaynor M. and S. Polachek (1992) "Measuring Information in the Market: An Application to Physician Services," Unpublished manuscript, Johns Hopkins University, Baltimore Md.

Hajivassiliou, Vassilis, Daniel McFadden, Paul Ruud (1992) "Simulation of Multivariate Normal Orthant Probabilities: Theoretical and Computational Results," unpublished manuscript, Yale University, New Haven.

Hajivassiliou, Vassilis (1992) "Simulation Estimation Methods for Limited Dependent Variable Models," in: Maddala, G.S., C.R. Rao, and H.D. Vinod (eds.) *Handbook of Statistics*, Vol. 11, North Holland.

Hausman, J.A. and D.A. Wise (1978) "A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences," *Econometrica*, 46(2), 403-426.

Horowitz, J.L, J.M. Sparmann, and C.F. Daganzo (1982) "An Investigation of the Accuracy of the Clark Approximation for the Multinomial Probit Model," *Transportation Science*, 16(3), 382-401.

Keane, M.P. (1992) "A Note on Identification in the Multinomial Probit Model," *Journal of Business & Economic Statistics*, 10(2), April, 193-200.

Kenkel, D. S. (1990) "Consumer Health Information and the Demand for Medical Care."*Review of Economics and Statistics,"* 72(4), November, 587-595.

Kenkel, D. S. (1991) "Health Behavior, Health Knowledge and Schooling," *Journal of Political Economy,"* 99(2), April, 287-305.

Kwoka, J. (1984) "Advertising and the Price and Quality of Optometry Services," *American Economic Review,"* 74:211-216.

Lee, L.F. (1992) "On Efficiency of Methods of Simulated Moments and Maximum Simulated Likelihood Estimation of Discrete Response Models," *Econometric Theory*, 8, 518-552.

Lerman, S.R. and C.F. Manski (1981) "On the Use of Simulated Frequencies to Approximate Choice Probabilities," in: C.F. Manski and D. McFadden (eds.) Structural Analysis of Discrete Data with Econometric Applications, MIT Press, Cambridge, MA.

McFadden, D. (1981) "Econometric Models of Probabilistic Choice," in: C.F. Manski and D. McFadden (eds.)Structural Analysis of Discrete Data with Econometric Applications, MIT Press, Cambridge, MA.

McFadden, D. (1989) "A Method of Simulated Moments for Estimation of Discrete Response Models without Numerical Integration," *Econometrica*, 57(5), 995-1026.

McCall, N., T. Rice, and J. Sangl (1986) "Consumer Knowledge of Medicare and Supplemental Health Insurance Benefits," *Health Services Research*, 20(6), 633-657.

Monheit, A. and C. Schur (1989) Health Insurance Coverage of Retired Persons, (DHHS Publication No. 89-3444), National Medical Expenditure Survey Research Findings 2, National Center for Health Services Research and Health Care Technology Assessment. Rockville, Maryland

Neipp J. and Zeckhauser R (1985) "Persistence in the Choice of Health Plans," in Scheffler, R. M., and Rossiter, L. F., eds. Advances in Health Economics and Health Services Research, Vol. 6, JAI Press, Greenwich, Conn., 1985, 47-72.

New York Times (1991) "Elderly Get New Protection on Health Insurance."Nov. 5, Section A,7.

Pakes, A. and D. Pollard (1989) "Simulation and the Asymptotics of Optimization Estimators," *Econometrica*, 57(5), 1027-1057.

Pauly M. and M. Satterthwaite (1981) " The Pricing of Physician Services: A Test of the Role of Consumer Information," *Bell Journal of Economics*, 12:488-506.

Rankin, D. (1988), "Is Medigap Insurance Still Necessary," *The New York Times*, Aug. 7.

Rice, T., N. McCall, and J. Boismier (1991) "The Effectiveness of Consumer Choice in the Medicare Supplemental Health Insurance Market," *Health Services Research*, 26(2), 223-246.

Rosen S., and P. Taubman (1979) "Notes on Information and Unproductive Consumption," mimeo, Department of Economics, University of Chicago.

Small, K. and H. Rosen (1981) "Applied Welfare Economics with Discrete Choice Models" *Econometrica*, 1:105-30.

Sofaer, S., B. Davidson, and N. Goodman (1990) "Helping Medicare Beneficiaries Choose Health Insurance: The Illness Episode Approach," *The Gerontologist* 30(3):308-315.

Stigler, G. (1961), "The Economics of Information," *Journal of Political Economy*, 69: 122-136.

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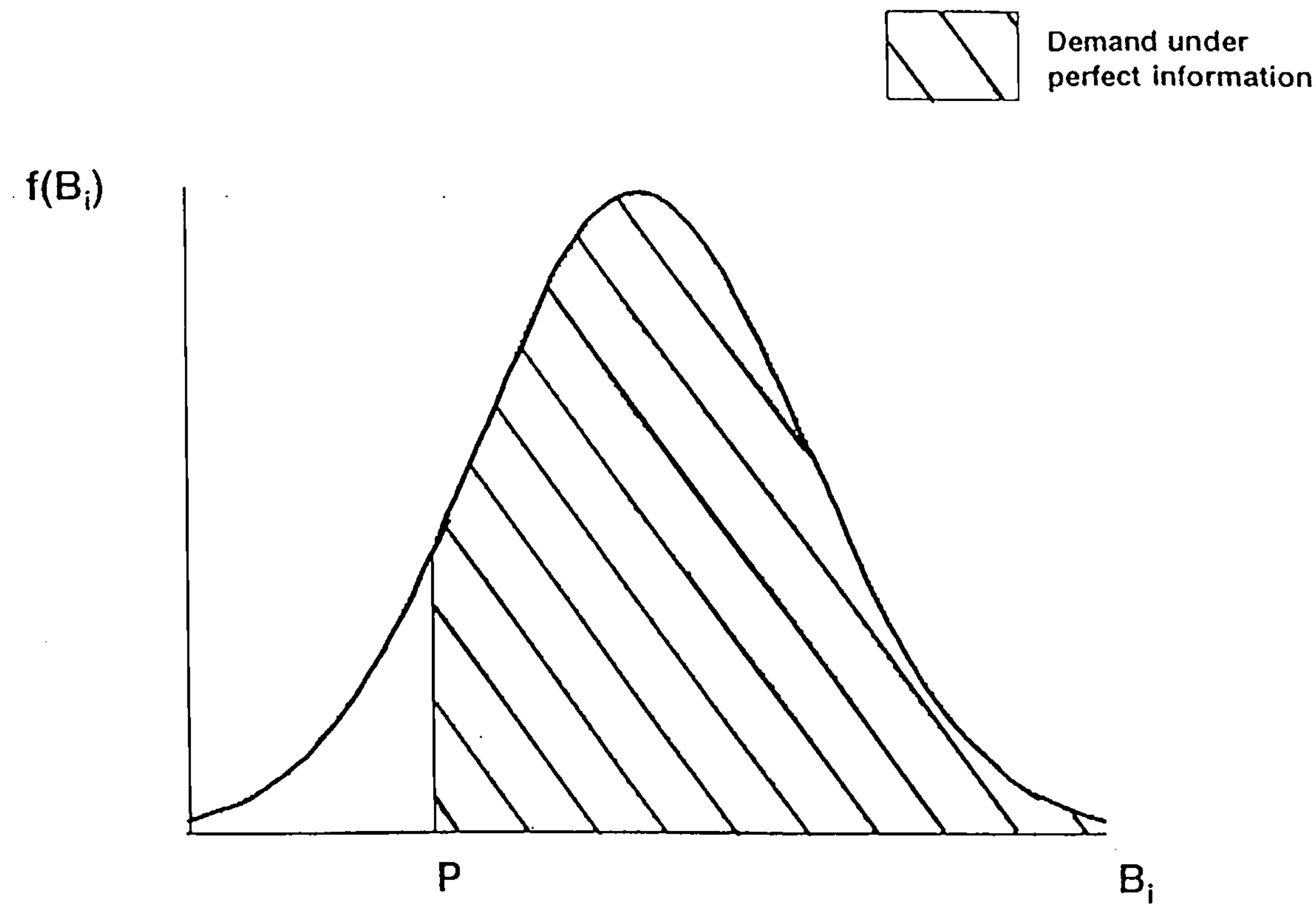

Figure 1. Demand for Supplemental Medicare Insurance: Perfect Information

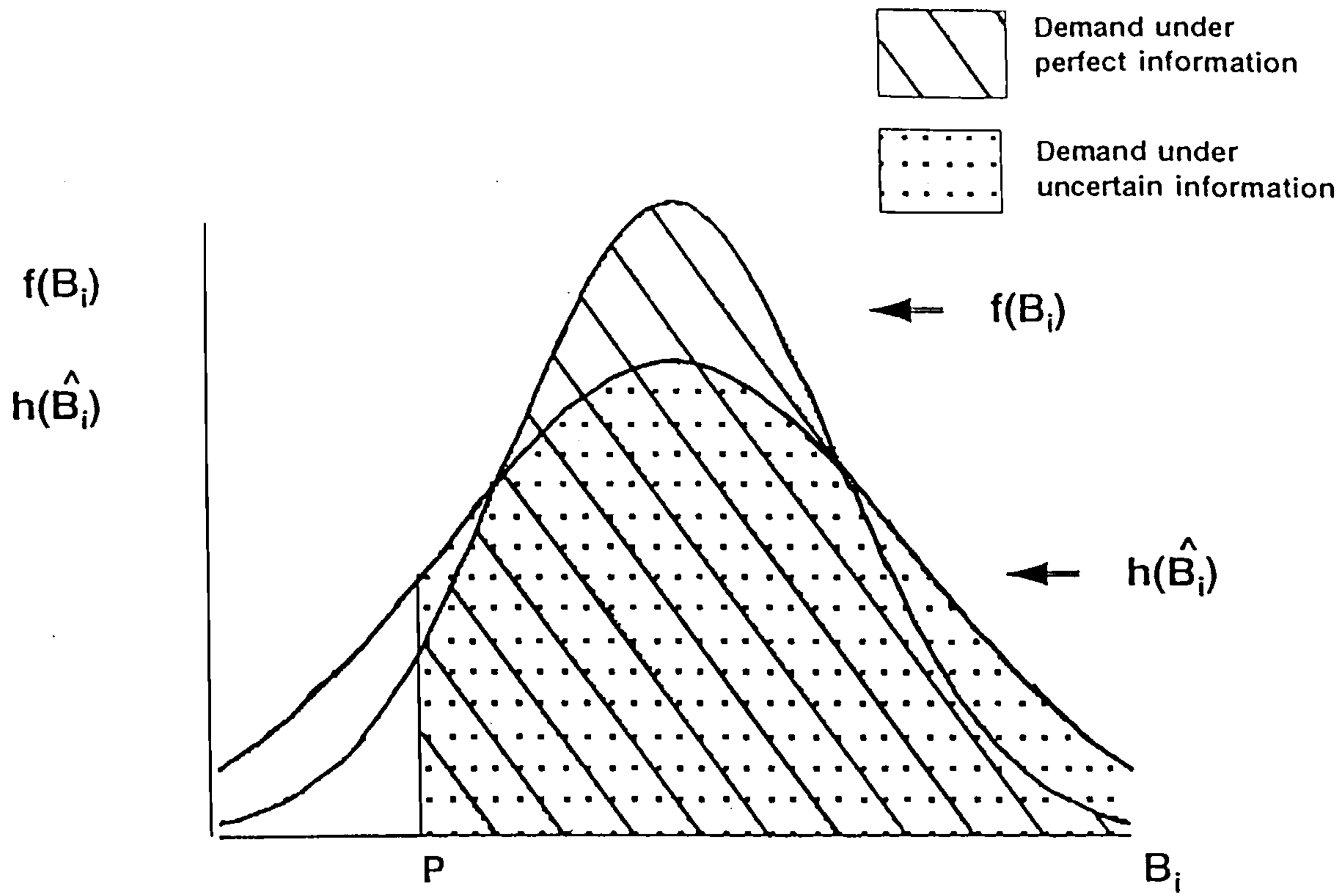

Figure 2a. Demand for Supplemental Medicare Insurance:
Effect of Imperfect Information When the Majority Purchase

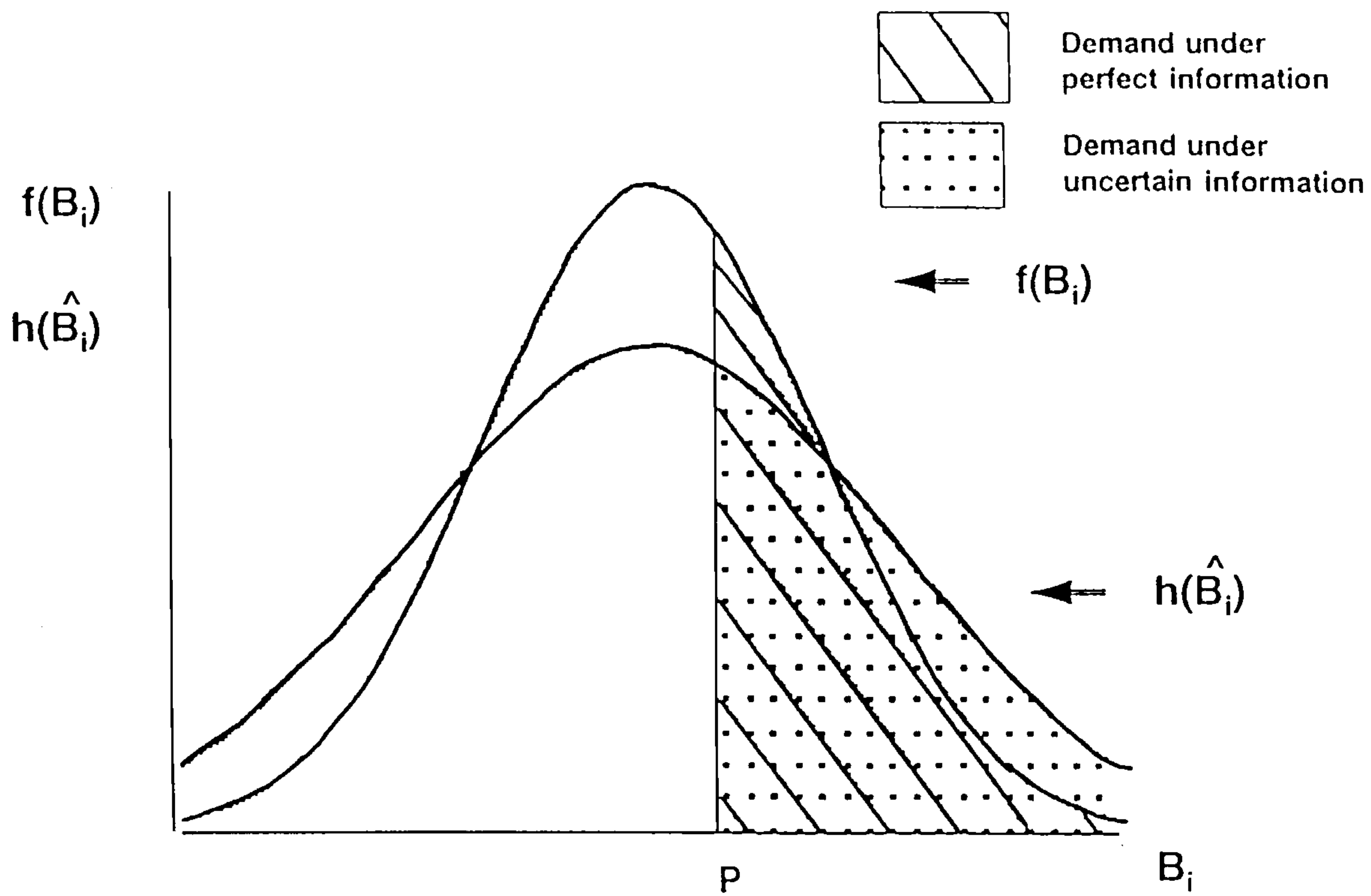

Figure 2b. Demand for Supplemental Medicare Insurance: Effect of Imperfect Information When a Minority Purchase