Home Care for the Disabled Elderly: Predictors and Expected Costs

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While interest in publicly funded home care for the disabled elderly is keen, basic policy issues need to be addressed before an appropriate program can be adopted and financed. This article presents findings from a study in which the cost implications of anticipated behavioral responses (for example, caregiver substitution) are estimated. Using simulation techniques, the results demonstrate that anticipated behavioral responses would likely add between $1.8 and $2.7 billion (1990 dollars) to the costs of a public home care program. Results from a variety of cost simulations are presented. The data base for the study was the 1982 National Long-Term Care Survey.

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Neither public nor private programs currently cover long-term care for most disabled elderly people living in the community. The growth of the elderly population coupled with the high costs of caring for elderly persons have stimulated interest on the part of Congress and the public in finding ways to provide and finance long-term home care.

Several long-term home care proposals have recently been put forward by federal policymakers (Shearer 1989). In 1987, for example, Congressman Claude Pepper introduced a major legislative proposal to provide publicly financed care at home for chronically disabled persons (U.S. Congress 1987). Last year, the Pepper Commission proposed a similarly far-reaching home care program (Pepper Commission 1990). These proposals and others highlight the interest on the part of Congress to expand home care benefits for the disabled elderly.

Although interest is intense, basic policy issues need to be addressed before a home care program can be adopted. One key issue surrounding the home care debate arises from concern that the use of home care services will increase if a publicly financed program is established. Policymakers are concerned that if a publicly funded program becomes available, would-be beneficiaries will increase their use of such services to an inappropriate degree because of the lower cost to them. They are also concerned that a home care program may encourage family caregivers of the elderly to substitute formal care for informal care.

To date, information has been limited regarding the effect of anticipated behavioral responses, such as caregiver substitution, on costs. As a first step toward filling this information gap, we present findings from a study in which we estimate the cost implications of two behavioral responses.

The study is based on data from a nationally representative survey of disabled, noninstitutionalized elderly persons. In the first of two basic parts we use these data to examine the relationship between personal and functional characteristics and formal home care use. To do this we employ regression analyses to identify the predictors of both home care use and home care quantity. In the second part of the study we use the regression results and simulation techniques to demonstrate policy applications of our regression results.

The article is organized to describe first the data source for the study. Next we present and discuss results from the regression analyses. We then present our simulation results and, subsequently, a discussion of the policy implications of our findings.

DATA SOURCE

Our analysis is based on data from the the 1982 National Long-Term Care Survey (NLTCS) (Macken 1986). Prospective survey respondents were first screened by telephone to identify disabled persons 65 and older. A detailed in-person interview was held with all noninstitutionalized persons who indicated during the telephone interview that they had needed help, or expected to need help, with basic activities of daily living (ADL) (for example, bathing or eating) or instrumental activities of daily living (IADL) (for example, meal preparation and housekeeping) for a period of three months or longer (Katz, Ford, Moskowitz, et al. 1963; Lawton and Brody 1969). Over 6,000 older disabled persons or their proxies completed the detailed questionnaire.

In the detailed survey, respondents were asked several questions about their personal characteristics such as age, sex, marital status, living arrangement, financial resources, and informal help. The survey also contained extensive detail on the ability of the respondents to perform basic activities on the ADL and IADL scale. In addition, the survey included questions to measure the cognitive and medical status of each person surveyed.

The NLTCS also collected data on home care use. As part of the survey, respondents were asked about their use of home care services during the week directly preceding the interview. For each paid helper, sample persons were asked what type of services the helper rendered, how often the helper performed those services, how long the helper had been providing the help, and who paid the helper.

Data from the NLTCS were used to conduct the regression analyses as well as the simulations. We present now the results from the first part of the study: the multivariate analyses of predictors of home care. We describe first the dependent variable and independent variables we tested; then we describe the estimation strategy and results.

PREDICTORS OF HOME CARE USE

DEPENDENT VARIABLE

The dependent variable for our analysis was the number of paid in-home visits per week. For an individual, the variable represents the total number of home care visits the person had received during a one-week period from paid helpers, regardless of payment source or helper

skill level. This information, as described earlier, was obtained during the interview.

In the survey population, about 19 percent of the respondents had a paid home care visit during the reference week. Among the users, most, 75.9 percent, had only nonskilled home care visits; 18.6 percent had only skilled home care; and 5.5 percent had both skilled and nonskilled home care. On average, users received 3.9 home care visits during the reference week.

INDEPENDENT VARIABLES

In our model, we tested several explanatory variables that have been found to affect the probability of using formal home care (McAuley and Arling 1984; Soldo 1985; Branch, Wetle, Scherr, et al. 1988; Liu, McBride, and Coughlin 1990). We included demographic characteristics, living arrangement, economic status, geographic location, availability of informal care, and health and functional status. We also included explanatory variables to account for market differences across geographic areas. Table 1 gives the definition, mean, and standard deviation of each independent variable we tested. While the definition of most variables is straightforward, some definitions require further elaboration.

Sociodemographics. The sociodemographic characteristics we included were age, sex, and race. We also included a variable that accounted for different living arrangements and one that counted a sample person's informal helpers. These variables—living arrangement and number of informal helpers—were intended to measure how much informal care a person had available.

Economic Status. We used three measures of economic status: income, home ownership, and Medicaid eligibility. Home ownership and Medicaid eligibility were entered as simple binary variables. For income, we used a variable that represents the ratio of monthly income of the sample person and his or her spouse to the poverty line. Sample persons were then grouped according to the categories specified in Table 1.

Functional and Health Status. One of the basic policy issues in the home care debate is how disability should be defined for purposes of program eligibility (Stone and Murtaugh 1990). In our analysis, we tried to approximate definitions currently being used in home care proposals. Our definition was: *if a person requires either hands-on or standby help in eating, dressing, toileting, transferring (getting into or out of bed or a chair), or bathing, then this person is considered dependent in the particular*

Table 1: Variable Descriptions

Variable	*Description*	*Mean**	*s.d.*
Dependent Variable			
	Number of paid home care visits received in one-week period	.751	–
Independent Variables			
Sociodemographic			
FEMALE	1 if sample person is female; 0 otherwise	.652	.476
WHITE	1 if sample person is white; 0 otherwise	.879	.327
AGE7584	1 if sample person is ages 75–84; 0 otherwise	.400	.490
AGEGT85	1 if sample person is age 85 or above; 0 otherwise	.182	.386
LIVSPOU	1 if sample person lives with spouse; 0 otherwise	.438	.496
LIVOTH	1 if sample person lives with other people (no spouse); 0 otherwise	.264	.441
INFHELP1	1 if sample person received help from one informal helper in reference week; 0 otherwise	.476	.499
INFHELP2	1 if sample person received help from two informal helpers in reference week; 0 otherwise	.207	.405
INFHELP3P	1 if sample person received help from three or more informal helpers in reference week; 0 otherwise	.107	.309
Economic status			
INCPOV12	1 if sample person and spouse combined income is between one and two times poverty level; 0 otherwise	.502	.500
INCPOV23	1 if sample person and spouse combined income is between two and three times poverty level; 0 otherwise	.159	.366
INCPOV3P	1 if sample person and spouse combined income is more than three times poverty level; 0 otherwise	.065	.246
HMOWNER	1 if sample person or spouse is a homeowner; 0 otherwise	.572	.495
MEDICAID	1 if sample person is Medicaid eligible; 0 otherwise	.233	.423
Functional and health status			
IADLONLY	1 if sample person has IADL impairment only; 0 otherwise	.379	.485
1-2ADL	1 if sample person requires personal assistance or supervision in one or two ADL; 0 otherwise	.277	.447
3-4ADL	1 if sample person requires personal assistance or supervision in three or four ADLs; 0 otherwise	.132	.338

Continued

Table 1: Continued

Variable	*Description*	*Mean**	*s.d.*
5ADL	1 if sample person requires personal assistance or supervision in five ADLs; 0 otherwise	.038	.191
SEVSEN	1 if sample person is severely cognitively impaired or if sample person is determined to be senile by a proxy respondent; 0 otherwise	.098	.297
NEUROL82	1 if sample person has multiple sclerosis, cerebral palsy, epilepsy or Parkinson's disease; 0 otherwise	.048	.214
CAFRST82	1 if sample person has had cancer, a fracture, or a stroke; 0 otherwise	.191	.393
Use of formal health care			
PRIHOS82	1 if sample person has had a hospital stay within the last 12 months; 0 otherwise	.378	.485
PRINH82	1 if sample person has ever had a nursing home stay; 0 otherwise	.075	.264
DRUGLT5	1 if sample person spent less than 5 percent of sample person's and spouse's combined monthly income on prescription drugs; 0 otherwise	.358	.479
DRUG5-10	1 if sample person spent between 5 and 10 percent of sample person's and spouse's combined monthly income on prescription drugs; 0 otherwise	.162	.368
DRUG10P	1 if sample person spent more than 10 percent of sample person's and spouse's combined monthly income on prescription drugs; 0 otherwise	.142	.349
Market			
METRO	1 if respondent lives in a metropolitan area; 0 otherwise	.693	.461
CERTBEDS83	Number of certified nursing home beds per 1,000 elderly in an MSA in 1983	50.868	21.639
USERVIS83	Number of home health visits per 1,000 users in an MSA in 1983	21.055	9.530

*Based on 4,699 observations.

activity. Then we created a scaled activities of daily living variable ranging from zero to five, where a score of zero indicates impairment in none of the five ADL while a score of five indicates impairment in all five ADL. We separated out further those persons who had no ADL impairments by placing them into one of two groups: (1) no ADL, but

deficiencies in performing instrumental activities of daily living, or (2) no ADL or IADL. In the regression, the omitted category was no impairment in either ADL or IADL.

The other functional status variable we included was a cognitive impairment measure. We used two sources of information to rate sample persons' cognitive status: test results from the Short Portable Mental Status Questionnaire (SPMSQ) and proxy responses regarding the sample person's cognitive ability. If SPMSQ results were available, then a person's cognitive status was rated following Pfeiffer's rules (Pfeiffer 1975). If no SPMSQ data were available, then a sample person's cognitive status was determined by the proxy's subjective judgment of his or her cognitive ability.

Prior Use of Health Care Services. Another group of predictors we included was prior use of health care services. One variable measured whether a person had had a hospital stay in the past year and another measured whether a person had ever been in a nursing home. We also included a variable that measured respondents' monthly out-of-pocket prescription medicine expenses relative to their monthly income. We expected to observe a negative relationship between drug expenses and home care use: given a limited disposable income, we reasoned that because most prescription medicines are critical to a person's health and functional well-being, people would spend money on prescription medicines before home care. From the ratio we constructed four binary categories; the category of no out-of-pocket expenses was omitted.

Market Variables. The final set of predictors we tested was market characteristics. We included three market variables to control for market conditions that might affect the use of home care. The first was a nursing home bed supply variable that counted the number of certified nursing home beds per 1,000 elderly in each metropolitan statistical area (MSA) in the country in 1983. (In each state, rural areas were combined and treated as a single unit.) The second market variable was the number of home health visits per 1,000 users in an MSA in 1983. This was intended to be a measure of the supply of home care providers. We aggregated to the MSA level because previous research had shown that the MSA best represented the market area for nursing home care and home health services (Kenney and Dubay 1990). The third was a variable indicating whether or not a person lived in a metropolitan area. This variable was included to measure individuals' access to home care; that is, we hypothesized that persons living in metropolitian areas would have greater access to home care than those living in nonmetropolitian areas.

ESTIMATION

The purpose of the estimation model was to derive a relationship between an individual's characteristics and his or her total formal home care use. The estimation was complicated by the fact that a large proportion of the NLTCS respondents (about 80 percent) did not use any home care during the week before the interview. This problem is described as a "censored" dependent variable, that is, the dependent variable is censored at zero for a large portion of the sample. If ordinary least squares (OLS) estimation techniques were used to estimate a regression function with a censored dependent variable, the results would be biased. As an alternative, Tobin (1958) developed the Tobit estimation procedure for the estimation of a regression function with a censored dependent variable. Following Maddala (1983), the Tobit model was estimated here using maximum likelihood procedures.[1] Interpretation of the estimated coefficients from the Tobit model is not straightforward because of the nonlinearity of the model. Therefore, we used the estimated coefficients to derive the effects of a change in an independent variable on the expected use of home care. In brief, this derivation leads to a prediction of home care use by an individual with mean characteristics for every independent variable except for the variable of interest. The predicted use of home care is an unconditional measure of use; that is, it is equal to the product of the probability of use and the expected level of use given that the individual is a user of home care.

In this section, we present results from the Tobit estimation. We first present our model and discuss the overall estimation results. Then, for those variables that were statistically significant, we present expected probabilities of use and number of home care visits. The results from the estimation model are shown in Table 2. Estimated parameter values and *t*-statistics are given for all variables; statistically significant variables are noted.

OVERVIEW OF ESTIMATION RESULTS

We found several variables to be significant predictors of home care use with the most important being age, living arrangement, number of informal helpers, income, and functional status. For example, age was a positive and significant predictor of home care use. By contrast, use of paid home care decreased with the greater availability of informal care, as indicated by the negative coefficients of the living arrangement and informal helper variables.

Table 2: Tobit Estimation Results

Variable Name	*Coefficient*	*t-Statistic*
Sociodemographic		
FEMALE	0.957*	3.20
WHITE	0.116	0.28
AGE7584	0.717*	2.50
AGEGT85	1.691*	4.70
LIVSPOU	-3.534*	-9.71
LIVOTH	-3.196*	-9.12
INFHELP1	-4.191*	-11.65
INFHELP2	-4.294*	-10.43
INFHELP3P	-4.914*	-9.81
Economic Status		
INCPOV12	1.746*	5.33
INCPOV23	2.653*	5.57
INCPOV3P	3.380*	5.69
HMOWNER	-0.375	-1.34
MEDICAID	1.062*	3.31
Functional and health status		
IADLONLY	4.233*	9.31
1-2ADL	6.610*	13.40
3-4ADL	8.668*	15.32
5ADL	10.437*	14.33
SEVSEN	-0.138	-0.32
NEUROL82	1.295*	2.48
CAFRST82	-0.092	-0.29
Use of formal health care		
PRIHOS82	1.650*	6.24
PRINH82	1.868*	4.64
DRUGLT5	-0.483	-1.56
DRUG5-10	-0.614	-1.59
DRUG10P	0.614	1.55
Market		
METRO	0.117	0.41
CERTBEDS83	-0.004	-0.76
USERVIS83	0.018	1.39
CONSTANT	-8.622	-9.82
SIGMA	5.762	36.87
Number of observations		4,699
Ending log-likelihood		-4,046.8
Log-likelihood (slopes = 0)		-10,132.3
Mean of dependent variable		.751
Proportion with zero expenditures		.806

*Significant at the 95 percent confidence level.

As expected, the ADL variables were strong predictors of formal home care use. Also, prior hospital stays and prior nursing home stays were strong predictors of formal home care use. We observed no difference in use between the cognitively impaired and the cognitively intact. This result was somewhat surprising in that, given the disease course of the impairment, we had expected a significantly higher use rate for the cognitively impaired. Since cognitive impairment is not a significant predictor after controlling for other health status measures, this result appears to suggest that medical conditions and ADL limitations may be stronger predictors of need for home care. Although it is possible that the effect of cognitive impairment in the regression is being captured by these other health status indicators, we found no statistical evidence to support an interactive effect between these variables.[2] The model showed no significant relationship between out-of-pocket expenses for drugs and home care use. This result seems to suggest that drugs are neither substitutes nor complements for home care use. On the other hand, if drug expenses reflect a person's health status, then the result may reflect the much stronger effect of the medical condition and ADL variables. Statistical tests of the correlation between these variables or tests of interaction in the multivariate model, however, do not support this hypothesis.

Finally, all of the market variables that we tested were insignificant, most likely because use of home care is driven by a person's personal and health status; that is, if a person needs home care, he or she will secure it regardless of the market condition.

EXPECTED PROBABILITIES OF USE AND NUMBER OF VISITS PER WEEK

Table 3 presents the probability of use (.160 per average respondent) and the expected number of home care visits (.484 on the average) per week.

Looking at the effect of individual characteristics on statistics for the average respondent (first line), the results show that women were more likely to use home care services than men. Our model indicated that living arrangement plays an important role in whether or not a person used home care. As expected, we found that those living alone had the highest probability of use: .281. The expected use rate of persons who lived with others was less than half this. We also found that for those who lived with others, the person they lived with made a difference in their expected use of services: respondents who lived with

Table 3: Effect of Individual Characteristics on Probability of Use and Expected Number of Visits

	*Probability of Use in Week**	*Expected Number of Visits in Week**
Average Respondent	.160	0.484
Demographic Characteristics		
Male	.135	0.392
Female	.174	0.539
Age 65–74	.136	0.396
Age 75–84	.165	0.504
Age 85+	.210	0.686
Lives alone	.281	1.003
Lives with spouse	.116	0.327
Lives with others	.128	0.369
0 informal helpers	.343	1.319
1 informal helper	.129	0.371
2 informal helpers	.125	0.358
3 or more informal helpers	.104	0.287
ADL Dependency† and Health Status Variables		
No ADL or IADL	.032	0.071
IADL only	.131	0.377
1-2 ADL	.238	0.808
3-4 ADL	.362	1.421
5 ADL	.481	2.166
No neurological illness	.157	0.474
Neurological illness	.217	0.715
No prior hospital stay	.135	0.392
Prior hospital stay	.207	0.671
No prior nursing home stay	.154	0.462
Prior nursing home stay	.243	0.829
Income Level Variables		
Monthly income		
Less than or equal to poverty line	.104	0.286
100%-200% poverty level	.170	0.522
200%-300% poverty level	.212	0.694
More than 300% poverty level	.251	0.862
Not Medicaid eligible	.149	0.446
Medicaid eligible	.196	0.629

*The calculation of the probabilities and expected number of visits assumes that all characteristics of the respondent are equal to their mean values except for the changes in the characteristic specified. Results are shown only for variables for which the corresponding coefficient was found to be statistically significant.

†ADL dependency includes person receiving either hands-on or supervisory help.

their spouses had a lower expected use rate than those who lived with individuals other than their spouses (.116 to .128).

The results indicate a direct, negative relationship between number of informal helpers and use of home care. People who had no informal helpers had one of the highest overall probabilities of use: .343. In a given week, the model predicts that persons with no helpers would be expected to use 1.3 visits, about three times the average. At the other extreme, people with three or more helpers had only a .104 probability of using home care.

Table 3 shows that level of ADL impairment was strongly associated with use of home care services. Persons who had five ADL had the highest probability of use, .481, and, correspondingly, the highest expected number of visits, 2.2. The same figures for persons with one or two ADLs were .238 and .808, respectively. It is interesting that IADL impairment alone substantially increased the probability of use: the expected probability of use for persons with impaired IADL only was nearly three times that of persons with no impairment.

Recent use of a hospital or prior use of a nursing home also significantly increased the chance of using home care. A person who had had a hospital stay within the past 12 months had over a 21 percent probability of using home care, whereas a person without a recent stay had a 13.5 percent probability. Likewise, individuals with a history of nursing home use had a higher probability of using home care than did individuals with no such history.

Our results demonstrate that a person's economic status plays a major role in predicting use of home care. We found that as income increased, the expected probability of home care use increased. For example, persons with incomes less than or equal to the poverty line had about a .104 probability of use whereas persons with incomes more than 300 percent over the poverty line had a .251 probability. Our dependent variable may, in part, explain why we found such a strong relationship between financial status and home care use. Although our dependent variable combined both skilled and nonskilled home care, the bulk of it was nonskilled care, which is not normally reimbursed by public or private insurers. Thus, much of the care that is being measured by the dependent variable reflects care that most likely had to be paid out-of-pocket by the sample person or that person's family.

Finally, whether a person was Medicaid eligible or not affected the probability of use: those who were eligible were more likely to use home care than those not eligible. The positive coefficient for Medicaid seems to contradict the income results. However, since we are already controlling for income, this variable simply tests whether a

Medicaid-eligible person used more home care than a non-Medicaid-eligible person. The combined results of income and Medicaid eligibility are noteworthy. They suggest that low-income people who are not eligible for Medicaid have a very low probability of using home care. This implies that this elderly subgroup is either getting no home care or is imposing a substantial burden on informal caregivers.

POLICY APPLICATIONS

In this section, we illustrate how our research results might be applied to policy analysis. Using the parameter estimates from the Tobit equations presented earlier we simulate the costs of some anticipated behavioral responses to the institution of a home care program. Before we discuss our simulation results, we briefly describe the simulation methods.

SIMULATION METHODS

The purpose of the simulation presented here was to provide estimates of the size of the population eligible for a publicly financed home care benefit, the use of home care within this population, and the cost of providing publicly financed home care to this population. Since the NLTCS is a representative sample of the population of potential users of home care within the United States, this sample was used in conjunction with the sample weights to provide national estimates of the effects of a home care program.

Using the NLTCS sample as an input file, the estimation of home care use under a public program was made in three steps. First, a determination of eligibility for the program was made for each person in the file. Second, an estimate of the amount of home care used once the program is in place was made for each person. Finally, national estimates of home care use were made by using sample weights to derive population estimates. These steps are discussed in detail here.

Eligibility. For the sample of potential users of home care, it was first necessary to determine whether they would be eligible for a publicly financed home care program. We considered two alternative eligibility criteria that led to different estimates of the number of "program eligibles": required functional impairment and restrictions on income. As for functional impairment criteria, a person was eligible only if he or she was cognitively impaired or had three or more ADL limitations requiring hands-on or standby help. We chose this combination of

functional criteria because it was advocated by the Pepper Commission.

We examined three alternative income eligibility criteria. The first of these was universal eligibility for all persons regardless of income. The second restricted eligibility to persons with incomes equal to or below 200 percent of the poverty level. Finally, we assumed that eligibility was restricted to persons with incomes equal to or below 100 percent of the poverty level.

Usage Estimates. The next step in the simulation analysis was the estimation of home care use for each sample person. Here, two alternative assumptions were made about the use of home care. In the first, the "base case," we assumed that the behavior of individuals would not change in response to the implementation of the program; that is, people would continue to use the same amount of home care as they were observed using during the interview period.

Under the second assumption, we assumed that the behavior of individuals covered by a new publicly-financed home care program would change. Although it is impossible to predict the exact behavior of individuals in the presence of such a program, the Tobit estimation results presented in the previous section provide a basis for estimating the increase in people's use of home care in response to a publicly subsidized program. In our simulations we assume that individuals could increase their use for two reasons. First, because the amount that an individual would have to pay out-of-pocket would drop, use of home care could be expected to increase. And, second, home care use could be expected to increase due to substitution of formal care for informal care.

The most straightforward way to estimate increased use due to a drop in out-of-pocket payment would have been to include a price variable in the regression. Unfortunately, home care price data at the MSA level are not available. To overcome this problem, we simulated individuals' responses to a change in the price of home care by using the effects of income on demand. The reason for using a change in income as a proxy is that home care provided at a zero price can be seen as similar to providing individuals with a lump-sum income supplement. To simulate this "price effect," we assumed that each individual in the sample would use home care at the same level as a person in the highest income bracket in the sample—greater than or equal to three times the poverty level. We chose the highest income bracket because we assumed that the response of lower-income elderly to a drop in the price of home care would be greater than the response of high-income elderly to such a change.

Another possible effect of a public home care program is the substitution of formal care for care that would otherwise be provided by family and friends. Given that family and friends provide the bulk of long-term care to the disabled, noninstitutionalized elderly, the substitution of formal for informal care could have a major effect on the cost of a home care program (Liu, Manton, and Liu 1985; Stone, Cafferata, and Sangl 1987).

Caregiver substitution could occur in one of two ways. First, formal care could fully or partially displace services provided by an informal caregiver. Alternatively, it could supplement informal care (Christianson 1988). Only a few studies have examined the effects of formal care on informal care and the exact relationship between them is not clear (Greene 1983; Kemper, Applebaum, and Harrigan 1987, Christianson 1988; Weissert, Cready, and Pawelak 1988; Edelman and Hughes 1990). In any case, the Tobit model results described earlier suggest that a reduction in the number of caregivers results in an increased demand for formal care.

Given the uncertainty concerning the effects of free formal care on the provision of informal care, we made three alternative assumptions designed to capture the range of possible caregiver effects. We described them as minimal, moderate, and large caregiver effects. Using past research findings on informal caregivers as a guide, we used two criteria to model the caregiver effects: whether the caregiver lived with the sample person and the relationship between the caregiver and the sample person (for example, spouse, relative, nonrelative). Under the minimal caregiver effect scenario, it was assumed that all caregivers who were not relatives and who did not live with the disabled person would stop providing care after a home care program was established. Under the moderate caregiver effect scenario, it was assumed that only those caregivers living with the sample person would continue to provide care; all other caregivers stopped providing care. In the most extreme case—the large caregiver effect scenario—it was assumed that only spouses continued to provide care. A summary of the behavior changes assumed in the simulations is given in Table 4.

National Estimates. To derive estimates of total recipients and total costs we made use of sample population weights and an estimate of the costs of providing home care. The population weights provided with the NLTCS were used here, except that some adjustments in these weights were made to account for persons dropped from the sample because of nonresponses to crucial questions in the survey. (See the Appendix for a discussion of the reweighting procedures.)

Although the NLTCS collected detailed information on home care

Table 4: Summary of Behavioral Change Assumptions Used in Simulations

Scenario	*Income Assumption*	*Caregiver Assumption*
Base case	Same as actual	Same as actual
Price effect	Income/Poverty level ≥3.0	Same as actual
Minimal caregiver effect	Same as actual	All household caregivers and non-household, relative caregivers remain
Moderate caregiver effect	Same as actual	All household caregivers remain; all non-household caregivers stop providing care
Large caregiver effect	Same as actual	Only spousal caregivers continue to provide care

use, it did not collect corresponding information on the costs associated with such care. We used another data source, which did contain home care cost data, to supplement our analysis. We obtained home care cost data from the 1981–1982 National Long-Term Care Channeling Demonstration.[3] For our analysis, we used a home care visit cost of $24.28 (1982 dollars).[4]

Base Case. Table 5 presents results of the simulation, including estimates of the number of expected users, program participation rate, and expected annual costs for each of the three income eligibility thresholds. The first line describes the "base case," which is the estimated usage if the program were implemented and behavior of eligible persons did not change in response to the program. The table shows that if a universal entitlement program was established and behavior remained consistent, the expected number of weekly users would be close to 350,000 and the participation rate would be nearly 30 percent. The cost of such a program was estimated at $3.2 billion. Corresponding base case statistics are also given for programs that used income as an eligibility criterion.

Price Effects. The first behavioral response we simulate here is a "price effect." The results, shown in line 2 of Table 5, demonstrate that such an effect could substantially increase the costs of a home health program. Part of this increase would occur because of increases in the participation rate in the program, as an additional 10 percent of the eligible—almost 100,000 persons—would participate in a universal entitlement program as a result of the decrease in their out-of-pocket costs. Costs would also increase because people who are already users

Table 5: Simulation Results: Impact of Select Program Effects on Expected Number of Users per Week, Participation Rate, Total Number of Annual Visits, and Expected Costs

	Income Eligibility Standard											
	Universal Entitlement				*200% of Poverty Line*				*100% of Poverty Line*			
Assumed Behavioral Response	*Expected No. Users per Week (000s)*	*Participation Rate**	*Total Annual Visits (000s)*	*Expected Costs (Billions 1990$)†*	*Expected No. Users per Week (000s)*	*Participation Rate**	*Total Annual Visits (000s)*	*Expected Costs (Billions 1990$)†*	*Expected No. Users per Week (000s)*	*Participation Rate**	*Total Annual Visits (000s)*	*Expected Costs (Billions 1990$)†*
Base case	347.9	0.31	1,477.7	$3.2	270.1	0.30	1,147.4	$2.5	83.8	0.25	335.9	$0.7
Price effect	470.2	0.41	2,248.5	4.9	385.4	0.43	1,870.6	4.1	145.2	0.44	719.2	1.6
Caregiver effects												
Minimal	352.1	0.31	1,509.0	3.3	273.7	0.31	1,174.8	2.5	84.6	0.26	340.9	0.7
Moderate	391.3	0.34	1,842.7	4.0	309.3	0.34	1,482.9	3.2	97.4	0.30	441.7	1.0
Large	503.2	0.44	2,605.1	5.7	414.9	0.46	2,193.3	4.8	147.8	0.45	750.7	1.6
Combined price and caregiver effects												
Minimal	474.3	0.42	2,287.6	5.0	388.8	0.43	1,913.4	4.2	146.1	0.44	727.3	1.6
Moderate	511.6	0.45	2,702.5	5.9	422.5	0.47	2,300.7	5.0	158.0	0.48	870.6	1.9
Large	626.2	0.55	3,737.3	8.1	530.8	0.59	3,280.8	7.1	211.3	0.64	1,358.8	2.9

*The participation rate is defined as the ratio of the number of expected users per week to the total number of persons eligible.

†Expected annual costs are calculated using an assumed annual inflation rate of 7 percent.

of the program would respond by increasing the number of home health visits. The result would be an increase from 1.5 to 2.2 million in the number of total visits and $3.2 to $4.9 billion in costs.

The increase in use among eligibles would be even larger under a program restricted to only persons below 200 percent of the poverty level, as reflected by an increase in users in excess of 115 thousand, an increase in the participation rate to 43 percent, and an increase in total visits to 1.9 million. Although a price effect would add fewer users to a program restricted to near-poverty-level persons, the participation rate would increase substantially, from 25 to 44 percent, and the costs of the program would increase by more than 100 percent, from $700 million to $1.6 billion.

These results demonstrate that the combination of new users and increased intensity of use by others would result in a participation rate of almost two-fifths of the eligible disabled elderly and increases in program costs of between 50 and 100 percent.

Substitution Effect. One fear of policymakers is that public provision of formal home care services would lead to a substitution of formal paid care for services currently provided by informal caregivers. Table 5 presents three alternative estimates of these effects.

If the effect of the program on caregivers is small (for example, if only caregivers who are not relatives and who are living outside the household stop providing care), the simulations demonstrate that only a negligible increase would occur in the use of paid home care. As compared to the base case, the increase in the number of visits would be fewer than 20,000 per week and the increase in costs would not exceed $100 million.

In contrast, the expected effects of the decrease in use of caregivers would be large under the moderate and large caregiver effect scenarios. If all non-household caregivers were to stop providing care (the moderate caregiver scenario), then the expected increase in costs would be $700 million under a universal entitlement program for the program limited to persons below 200 percent of poverty, and $300 million under the program limited to poverty-level elderly. The expected increase in use would be greatest under the large caregiver effect scenario, which assumes that only spousal caregivers would continue to provide care. Under a universal entitlement program, an additional 1.2 million visits would be made each week (relative to the base case). In addition, costs would increase from $3.2 to $5.7 billion (Figure 1). We found that the caregiver effect is largest for the poor and near-poor. For example, if the program used a more limited income

eligibility criterion, the number of visits used and total costs incurred would increase by 90 to 130 percent.

These results suggest that substitution of formal care for informal care, if it occurs, could substantially increase the costs of a home care program. The expected increase in use or costs would depend on the size of the caregiver effect. The three caregiver scenarios presented here provide a range of possible estimated effects of caregiver substitution on the costs of a home care program.

Combined Price and Caregiver Effects. One possible result from the creation of a home care program is that the behavior of the disabled elderly would change in two ways—they would increase the use of home care as a result of both the price and caregiver effects. The final three lines of Table 5 present the results of simulations that demonstrate these combined effects.

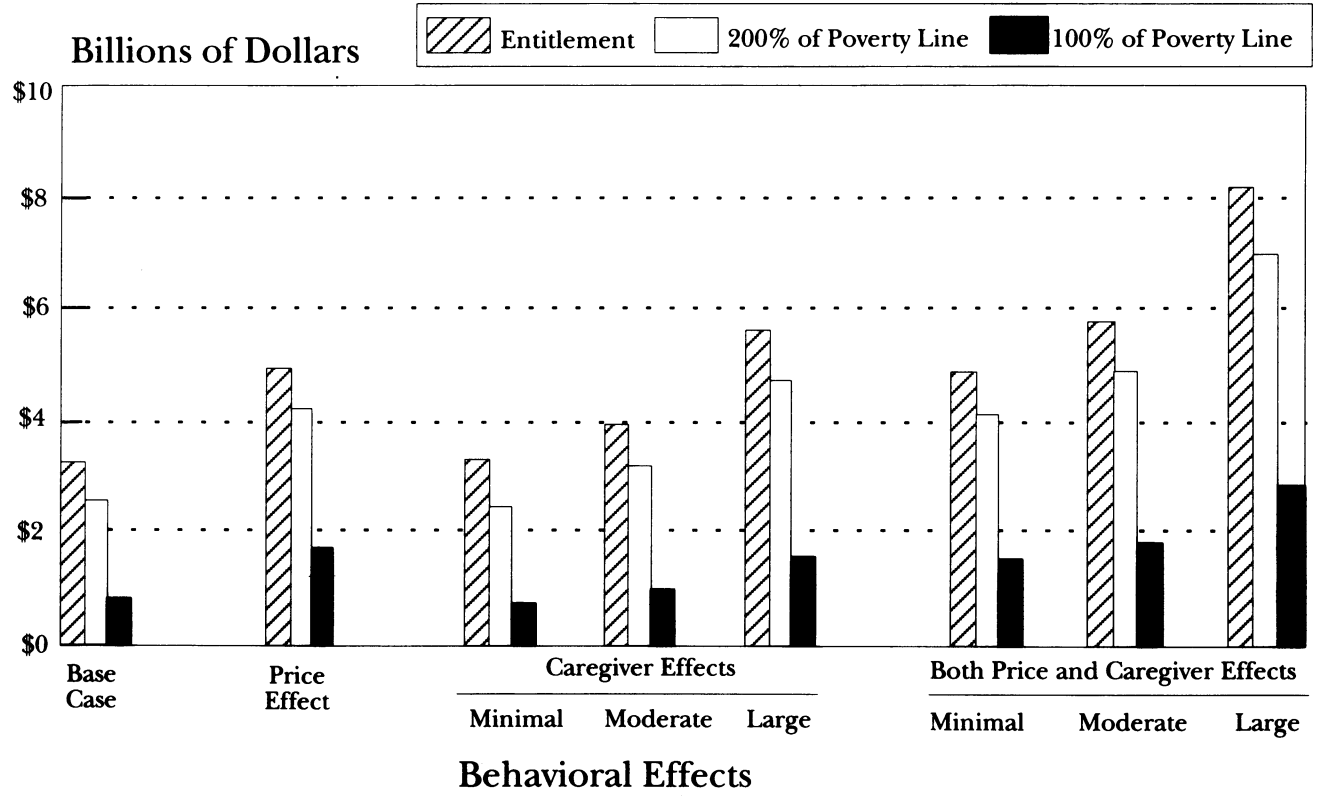
As expected, the use of a home care program would be greatest if it were assumed that both behavioral responses would occur. For example, expected annual costs would increase from $3.2 billion under the base-case universal entitlement program to between $5.0 billion and $8.1 billion, depending on the assumed caregiver effect (Figure 1). The number of users would increase by between 36 and 80 percent (Table 5), reflected in an estimated participation rate under these scenarios that would increase to between 42 and 55 percent. These participation rates, while large, are not out of line with the participation rates experienced under other government programs.[5]

If eligibility under the program is limited to the disabled elderly under 200 or 100 percent of the poverty line, then the expected increase in costs would be lower than under the universal entitlement program. However, the expected effects of the two behavioral changes would still be large. For example, costs would increase from $2.5 billion to between $4.2 and $7.1 billion under a program limited to persons below 200 percent of the poverty line, and from $700 million to between $1.6 and $2.9 billion under a program limited to only the disabled elderly in poverty (Figure 1). The estimates demonstrate that between 43 and 64 percent of the eligible disabled elderly would participate under each of these scenarios (Table 5).

DISCUSSION

In this study we developed a model that predicts home care use among the frail elderly. We then used this model to simulate the cost implications of various program eligibility criteria and some anticipated

Figure 1: Expected Costs of Home Health Care under Different Behavioral Scenarios



behavioral responses to a home care program. The NLTCS provided a good data source for these analyses because it was a nationally representative survey of disabled elderly persons living in the community—the target population if a publicly financed home care program were established.

In general, our home care model agreed with past studies on the predictors of home care use. For example, consistent with other multivariate analyses, our results showed that increasing age and functional disability were positive predictors of home care use (Kemper, Brown, Carcagno, et al. 1988; Liu, McBride, and Coughlin 1990). Several of our findings, however, contradicted those of past studies (McAuley and Arling 1984; Soldo 1985). We found, for instance, that neither a person's home location—in an urban or nonurban area—nor the person's level of cognitive impairment significantly affected home care use. Perhaps most importantly, we found a strong positive income effect on home care use, in direct contrast to the reports of other researchers (McAuley and Arling 1984; Soldo 1985; Branch, Wetle, Scherr, et al. 1988).

Our results disagree with previous studies—and discrepancies exist among the previous studies—for several reasons. First, a range of definitions of home care, from nonskilled to skilled care, have been used. For example, our analysis used a dependent variable that combined skilled and nonskilled care, although the bulk of the care was nonskilled, whereas other studies examined predictors of skilled home care only. Other reasons for the discrepancies include omitted variable biases and different sample populations, as well as different methodologies.

Another reason for the discrepancies involves timing differences in the measurement of characteristics and measurement of use. In our analysis, virtually no time lag—one week—took place between the day when personal and functional characteristics were measured and the day when use of home care was measured. Alternatively, in a study completed by Branch and colleagues (1988), as much as a two-year lag could occur between the time when personal characteristics were measured and when home care use was measured. A long time lag may introduce some bias into the results as individual circumstances can change within a relatively short time period (for example, functional status may decline or a person may become widowed), particularly in a frail, elderly population. The fact that no time lag occurred in our study may explain why we found many variables to be highly significant predictors of home care use.

The simulation results demonstrated that anticipated behavioral

responses of the disabled elderly could have dramatic effects on the use and costs of a home care program. While a universal home care entitlement program would cost $3.2 billion if the behavior of the elderly did not change, the likely effect of behavioral responses by the disabled elderly would be to add between $1.8 and $2.7 billion to the costs of the program. For programs that would restrict eligibility to the poor or near-poor elderly, the combined behavioral responses of the disabled elderly would increase costs by between $1.0 and $2.5 billion. The exact response of the elderly to a home care program is not known a priori, of course, but our results present a range of estimates that could be useful in setting policy.

The costs presented here are illustrative and are not intended to reflect the full costs of a publicly financed program. In addition to the costs associated with benefits and possible behavioral responses, other costs (both positive and negative) need to be accounted for as well. Program administrative costs, for example, would need to be added, whereas Medicaid savings expected because of the program would need to be deducted. Similarly, assuming caregiver substitution did occur once a program was in place, some accounting of the savings in opportunity costs to informal caregivers would be needed. Costs would need to be further adjusted if beneficiary cost sharing were imposed.

Our estimates would also need to be adjusted to reflect changes in the home care market that have occurred since 1982, the year the NLTCS was conducted. For example, in late 1981 the 2,176 home and community-based waiver program went into effect. Also in 1981, Congress changed the Social Services program into a block grant program which, according to state surveys, has substantially altered spending on home care in some states (Lipson and Donohoe 1988). Moreover, there have been shifts in state-sponsored home care programs over the past decade. These and other changes that have occurred in the home health care market would directly affect our simulated cost estimates.

Our findings suggest that policymakers need to be mindful of other, indirect program costs, such as costs associated with anticipated behavioral responses, because these can have pronounced effects on program costs.

APPENDIX

As described in the text, a Tobit estimation procedure is used in this study. The results of the Tobit estimation can be used to estimate the usage of home care by representative persons in the NLTCS sample

(see McDonald and Moffitt 1980 for a full description of this procedure). In this article the estimation model is used to simulate the effects of a public home care program on the expected use of home care by individuals in the NLTCS. The work describes the results from this simulation. Here, the methods used to derive these estimates are described in detail.

Simulation Methods

The procedures used to simulate use of a national home care program, and its costs, were discussed in the text. The procedure required the development of estimates of home care use under alternative assumptions about the behavior of individuals in response to the home care program. Using these individual estimates and an indicator of eligibility, the users of home care were identified. The final step in reaching national cost estimates was to use weighting procedures to translate results from the NLTCS sample into national cost estimates.

The population weights used here were the weights provided with the NLTCS, adjusted to account for persons dropped from the sample because of missing data. To estimate home care use by the disabled elderly, the simulations required complete information on all of the variables included in the Tobit model. We were forced to drop a number of persons (over 1,300) from the sample who did not have information on any of these variables. Although this procedure is common in statistical analyses similar to this study, the dropping of people from the sample meant that the NLTCS population weights would no longer provide national estimates. To correct this problem, we adjusted the population weights to account for the excluded sample persons.

Before constructing adjusted sample weights, we studied our subsample to see whether there was or was not evidence to suggest that sample persons who had missing responses to crucial questions were systematically different from the rest of the sample. Because the original weighting procedure for the NLTCS was based on stratifications by age, sex, race, and region of residence, we chose to compare the full sample with the subsample using these characteristics. In comparisons of sample means from the full sample to the subsample, we found that the difference in the sample means was statistically different for race and age, but was not different for sex. These differences suggested that the simple solution of proportional reweighting was not acceptable. As an alternative, we calculated 12 reweighting factors that were specific to combinations of three factors: sex (male/female), race (white/nonwhite), and age (age 65–74, 75–84, and 85 or older). Each

reweighting factor (μs) was calculated as the simple ratio of the sum of the weights for each stratified subsample:

$$\mu_s = \sum_{i=1}^{N_s} W_{is} / \sum_{i=1}^{N_s^*} W_{is} \quad (1)$$

where

W_{is} = NLTCS weight for person i in stratified group s;
N_s = number of sample persons in the full sample from group s; and
N_s^* = number of sample persons in the subsample from group s.

The new population weight for person i in group s was then calculated as:

$$W_i^* = \mu_s W_i \quad (2)$$

where

W_i^* = adjusted sample weight for person i; and
W_i = original NLTCS sample weight for person i.

Before accepting these new weights, we also made an additional comparison of sample means. Because the first-stage estimation factor for calculating the original NLTCS weights was stratified using census region and SMSA/non-SMSA location, we also compared the weighted sample means in each of these eight categories. Through using the new subsample weights, a comparison of the eight sample means demonstrated that the sample means were not statistically different.

Although the changes in the weights described here should correct for most differences between the subsample and full sample, the national cost estimates presented in the article may still be somewhat biased by the exclusion of some sample persons. However, we reason that these adjustments account for most differences in the subsamples and that a more complex reweighting procedure was not justified by the statistical tests.

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NOTES

1. The LIMDEP estimation package was used to derive the Tobit estimates (Greene 1988).
2. Although we found some positive correlation between the level of cognitive impairment and the number of ADL limitations in the NLTCS sample, an interaction term between these two variables in the multivariate model did not prove to be statistically significant. This does not prove definitively that the insignificance of the cognitive impairment as a predictor variable is not explained by its correlation with the ADL variable; it does, however, suggest that other factors may explain the result.
3. Channeling, sponsored by the Department of Health and Human Services, was a ten-site demonstration to determine if comprehensive case management of community-based disabled elderly affected their risk of entering a nursing home. Two models of channeling were tested in the demonstration. One was a basic model in which only case management services were offered; the other was an enhanced case management program that offered expanded service coverage and payment. Participants were randomly assigned to either the treatment or control group. Over 6,000 older persons participated in channeling. Complete documentation on the demonstration has been described elsewhere (Kemper, Brown, Carcagno, et al. 1988). Although the unit cost was obtained from the Channeling project, any unit cost could be used in the simulation. In practice, a range of costs reflecting different home care program models—for example, from modest to enriched programs—could be substituted in our simulation model to estimate the effects of different unit costs.
4. This unit cost was constructed as follows. Using information from the first six months of the demonstration, price per visit for nonskilled home care (personal care and housekeeping services) and for skilled home care (skilled nursing, therapy, and home care) for controls only were extracted from the data set. Then a weighted average total home care unit cost was calculated where the weight adjusted for the proportion of nonskilled home care visits and skilled visits in the NLTCS population.
5. For example, approximately 58 percent of the elderly poor participate in the Supplemental Security Income (SSI) program (U.S. Congress 1990, 729); 49 percent of the poverty population participate in the Aid to Families with Dependent Children (AFDC) program (U.S. Congress 1990, 577); and 52 percent of children in poverty participate in the Medicaid program (U.S. Congress 1990, 1,283).

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