Dynamic Aspects of Prescription Drug Use in an Elderly Population

Bruce Stuart and N. Edward Coulson

Objective. This study explores longitudinal patterns in outpatient prescription drug use in an elderly population.

Data Sources/Study Setting. Enrollment records and prescription drug claims were obtained for a sample of elderly Pennsylvanians (N = 27,301) who had enrolled in the Pharmaceutical Assistance Contract for the Elderly (PACE) program at any time between July 1984 and June 1987.

Study Design. The study tracks monthly prescription fill rates for sampled PACE beneficiaries from their initial enrollment month through disenrollment, death, or the end of the study (whichever occurred first). We specify two-part multivariate models to assess the effect of calendar time, length of time in the PACE program, and progression to disenrollment or death both on the probability of any prescription use and on the level of use among those who filled at least one prescription claim per month. Control variables include age, gender, race, income, residence, and marital status.

Data Collection/Extraction Methods. Data were extracted from administrative files maintained by the PACE program, checked for errors, and then formatted as person-month records.

Principal Findings/Conclusions. We find a strong positive relationship between drug use and the length of time persons are PACE-enrolled. Persons whose death occurs within a year have much higher prescription utilization rates than do persons whose death is at least a year away, and the differential increases as death nears. Persons who fail to renew PACE coverage use significantly fewer prescription drugs in the year prior to disenrollment. Holding age and other factors constant, we find that average levels of prescription use actually declined over the study period.

Keywords. Prescription drugs, drug use among the elderly, pharmaceutical assistance programs

Health interview surveys conducted over the past two decades have produced important baseline data on prescription drug use patterns of elderly Americans (Grindstaff, Hirsch, and Silverman 1981; LaVange and Silverman 1987; Moeller and Mathiowetz 1989). With few exceptions these surveys are cross-sectional rather than longitudinal in design. Each provides a static picture of utilization behavior at the time (or some period before) the survey was administered. Any conclusions about changes in use over time must be inferred from natural variation within the sample itself (i.e., estimating the effect of aging on medicine use by comparing rates for respondents of different ages) or by comparing results across surveys. Both methods are limited in the information they convey.

This study uses a hybrid longitudinal/cross-section design to explore selected dynamic characteristics of outpatient prescription drug use in a population of elderly Pennsylvania residents enrolled in the state's Pharmaceutical Assistance Contract for the Elderly (PACE) program. Our objective is to show how prescription use varies with calendar time, duration of coverage, progression toward death, period before voluntary program disenrollment, and various interactions among these time-varying factors.

RELEVANCE OF THE TOPIC

Between 1980 and 1987, per capita spending on outpatient prescription drugs by the elderly grew by more than 14 percent per year (Moeller and Mathiowetz 1989), representing one of the fastest-growing components in the national health accounts. The rising cost of financing prescription drugs for this age group has concerned state government policymakers for more than two decades, first in the context of Medicaid, and more recently in that of state pharmaceutical assistance programs like PACE.

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The passage—and then repeal—of the Medicare Catastrophic Coverage Act of 1988 (P.L. 100-360) made it a national issue.

The history of P.L. 100-360 highlights the need for better longitudinal data on drug utilization patterns of the aged. Among other things, the lack of such a database seriously hampered the government's ability to produce accurate budget forecasts for the prescription drug provisions contained in the law (U.S. Congress 1989). By the time reasonably current data became available from the National Medical Expenditure Survey (NMES) in September 1989, the law was already in serious trouble. But even if the NMES survey results had been available earlier, they could not have answered two of the more critical policy questions facing government forecasters at the time: What caused drug spending by the elderly to grow at such a rapid rate during the 1980s? Were the factors that contributed toward this growth likely to influence future patterns of medicine use? Only a database with a longitudinal dimension can distinguish growth associated with historical events (which may or may not be repeated) from growth due to person-level changes in demand or care-seeking behavior (which presumably will continue to be a factor as the financing system evolves).

This study analyzes a longitudinal data set of 36 months duration extending from July 1984 through June 1987. Admittedly, this is a short time span from the standpoint of characterizing secular trends in the use of prescription drugs by the elderly. However, the length of time is enough to verify the existence of a trend and to demonstrate reasons why it is important to study individual utilization patterns in a dynamic context.

Many crucial policy questions relate to the behavioral dynamics of drug use. For example, directors of new or expanding third-party prescription drug programs need to understand the connection between drug utilization and the length of time that individuals have been insured because this relationship can affect the rate of growth in program budgets. Economists typically estimate the demand-inducing effect of insurance using cross-sectional databases that contain no observations for time or time-related variables. The validity of the procedure rests on the assumption that insured individuals have fully adjusted their consumption habits to the level of benefit coverage they maintain. But if there is a learning phase associated with new coverage, such estimates will provide a poor basis for forecasting budgetary requirements, at least during the initial period of program operations.

What policymakers need are estimates of *exposure-response*: that is, how individual utilization behavior changes from the time coverage begins to the point at which equilibrium levels are reached. Over the

longer term, it may also be important to know whether exposure-response rates remain stable. This is primarily a concern for voluntary programs where the characteristics of program entrants may change significantly from one period to another.

The present work measures program exposure by counting the number of months that pass between a beneficiary's initial PACE enrollment date and the service date on the prescription claim. The choice of a month as the exposure measure permits considerable flexibility in modeling phenomena related to beneficiary learning patterns.

The relationship between health services use and progression toward death has attracted considerable research interest (Lubitz and Prihoda 1984; Roos, Montgomery, and Roos 1987; Scitovsky 1989; Riley et al. 1987; Riley and Lubitz 1989; Long, Gibbs, Crozier, et al. 1984). We include a time-to-death variable in the present work both to permit comparisons with other studies on this subject, and to demonstrate ways in which our method can be used to develop event-related or episodic analyses of prescription drug use.

A final set of dynamic variables was chosen to explore program selection effects. As described shortly, PACE is a voluntary public program. Not all eligible persons decide to enroll, and among those who do, some fail to renew their PACE cards. By studying changes in utilization patterns of beneficiaries according to enrollment date and time to nonrenewal, we hope to gain a better understanding of program selection and disenrollment processes.

THE PENNSYLVANIA PACE PROGRAM

PACE is a lottery-financed pharmaceutical assistance program for Pennsylvania's elderly residents with annual incomes below $12,000 for single persons and $15,000 for married couples. Initiated on July 1, 1984, it is the largest of ten such state-level programs.[1] Enrollment is voluntary and no premium is required. To maintain continued coverage beneficiaries must reapply annually.[2] The average quarterly enrollment during 1989 was 444,000 (Pennsylvania Department of Aging 1990) or nearly one in every four Pennsylvanians over the age of 65.

The PACE program covers legend drugs, insulin, and insulin syringes on an outpatient basis, and also provides inpatient drug coverage for eligible nursing home residents. There is no restricted formulary, but prescription dosages are limited to 30-days supply or 100 units,

whichever is less. Beneficiaries on maintenance medications must therefore refill their prescriptions on a monthly basis.

PACE requires assignment of claims and pays pharmacies the lower of their usual and customary charge or the average wholesale price (AWP) plus a dispensing fee of $2.75 per script. During the time frame of this study, PACE imposed a $4.00 copayment for each prescription filled or refilled by a program beneficiary. The copayment (now $6.00) is subtracted from the pharmacy reimbursement amount.

SAMPLING DESIGN AND DATA SOURCES

A two-stage procedure was used to select a sample of PACE beneficiaries for this study. In the first stage, we selected a random 5 percent sample of persons enrolled in PACE at any time between July 1984 and June 1987 (N = 27,301). The second stage involved randomly selecting one month of program enrollment (our term is "exposure-month") for each person sampled. The unit of analysis is thus the person-month of PACE enrollment. The month is an appropriate unit of time given the PACE medication dosage restrictions just noted.

This sampling design produces what can best be described as an "interval" cross-section. There is only one observation per person as in the more traditional "point" cross-section, but the sample is representative of the population of PACE-insured over the entire 36-month period under investigation.[3]

The interval design makes a virtue of a problem that frequently arises in cross-sectional survey research, namely, the inability to collect information from all respondents for the same period of calendar time. It is not uncommon in large surveys for the response period to vary by several months or more, sometimes necessitating seasonal or other corrective adjustments to be made in the data. By contrast, in the interval cross-section design all events and person-specific characteristics are explicitly identified by calendar date. It is this feature that permits modeling of dynamic effects. There are also significant computational advantages to the approach, since interval cross-sections can be analyzed using the same statistical procedures appropriate for point cross-sections.[4]

The principal data sources for study are PACE enrollment and claims activity files. To produce the person-month values for prescription drug use, we aggregated PACE claims by calendar month based on date of service. The same procedure was used to assign enrollee characteristics to each person-month represented in the sample. Person-months

during which an enrollee was PACE-eligible for less than 15 days were excluded from the sample. Dates of death for individuals who died during the study period (or up to a year thereafter), were determined by matching Social Security numbers from the PACE enrollment file with data on decedents supplied by the Pennsylvania Health Department and the federal Health Care Financing Administration.[5]

EMPIRICAL MODEL

We analyze the dynamics of prescription use among PACE beneficiaries in the context of a conventional two-stage utilization model (Duan et al. 1983, 1984). The first stage is an equation for probability of use with a binary dependent variable distinguishing prescription users from nonusers.[6] The second stage is an equation for level of use estimated from the sample subset filling one or more prescriptions in a month. The econometric justification for the approach stems from the peculiar distributional characteristics associated with most forms of health services utilization that include prescription drugs, namely, significant numbers of nonusers and a highly right-skewed distribution among users.

The probability-of-use (first-stage) equation takes the form:

$$\text{Prob}(Rx)_{it} = \beta_0 + \beta_1 t + \beta_2 E_{it} + \beta_3 X_{it} + \mu_{it} \quad (1)$$

where $\text{Prob}(Rx)_{it}$ equals one if the individual, i, filled one or more prescriptions in the calendar month, t, and zero otherwise. E represents a vector of characteristics related to the timing and duration of PACE enrollment; X is a vector of individual attributes, and μ is the error term. Since the average probability of use differs significantly from .5, a logit or probit estimator is preferred over ordinary least squares. We chose logit based on ease of computation.

The level-of-use (second-stage) equation takes the form:

$$Rx_{it} = \gamma_0 + \gamma_1 t + \gamma_2 E_{it} + \gamma_3 X_{it} + e_{it} \quad (2)$$

where the dependent variable, Rx, represents the number of prescriptions filled by users and the explanatory variable set is the same as in the first-stage equation. This equation was estimated using ordinary least squares regression with the dependent variable transformed to logarithms. We chose the semilog specification because semielasticities are more likely to be constant parameters than are slopes (see Manning, Newhouse, Duan, et al. 1986),[7] notwithstanding the fact that retransformation from logs to the original scale is sensitive to heteroskedasticity in

the error term. We tested for heteroskedasticity using procedures described in White (1980).

As a final step we took the output from the two models to compute the predicted marginal contribution of each independent variable to prescription utilization rates for a benchmark group of PACE enrollees. In order to assess the effect of a regressor on the number of prescription claims filed by PACE enrollees over the study period, consider the factorization:

$$E(Y) = P(Y > 0)E(Y \mid Y > 0) \tag{3}$$

We can estimate the expected number of claims per month, $E(Y)$, by noting that the probability of any use, $P(Y > 0)$, is the fitted probability from the logit regression $\exp(\beta X)/[1 + \exp(\beta X)]$ where the βs are the estimates (rather than the true parameters). The expected level of use by users, $E(Y \mid Y > 0)$, is the fitted value of the logarithmic regression transformed in the standard way back to levels form, $\exp(\gamma X + \sigma^2/2)$, where σ^2 is the variance of the error term in the second-step regression.

The implicit assumptions are of normality and constant variance. We used Godfrey's (1988) version of the Jarque-Bera test of normality.[8] In the presence of heteroskedasticity in the equation for level of use by users[9] we ran a regression of the form

$$\hat{e}^2 = \delta X^2 + v \tag{4}$$

where the $\hat{e}$ refers to the estimated residuals from the second-step regression. Estimates of the δ vector provide consistent estimates of the effects of various independent variables on the variance and, through the transformation, on the prediction.[10]

Replacing σ^2 with its estimate δX^2 in the formula, and taking derivatives gives the marginal contribution of each independent variable to the expected value of monthly perscription claims *Rx* per PACE beneficiary,

$$\partial E(Y)/\partial X_j = \{[\beta_j /(1 + \exp(X\beta)) + \gamma_j + \delta_j X_j]\}[E(Y)] \tag{5}$$

The right-hand side of this equation can be readily decomposed to yield expected values for the two components of prescription utilization, namely, the probability of use and level of use by users.

VARIABLE SPECIFICATION

We now describe the variables entered into the model and the reasons for their selection. (Variable definitions, means, and standard deviations are shown in Table 1.)

The two dependent variables, RXUSER and USERRATE, indi-

Table 1: Variable Definitions, Mean Values, and Standard Deviations (N = 27,301)

Variable		*Mean*	*s.d.*
Dependent Variables			
RXUSER	The probability of use per PACE enrollee in the month	0.64	0.48
USERRATE	Average Rx claims per month for enrollees filing claims	3.00	2.21
Time-Varying Explanatory Factors			
TIME	Calendar month: July 1984 = 1; August 1984 = 2; etc. to June 1987 = 36	21.22	10.49
FSTYEAR	A binary variable indicating first-year enrollees. FSTYEAR = 1 if TIME < 13; 0 otherwise	0.25	0.43
EXPOSURE	Exposure month: month of initial PACE eligibility = 1; etc. to 36 for the 36th month of enrollment	12.65	9.64
MTD	Month to death = 0 if person's death is 12 months or more in the future; 1 if death is 11 months in the future; etc. to 12 if the person died in the month	0.886	2.72
MTNR	Month to nonrenewal = 0 if person was alive, PACE-eligible, and reenrolled on each PACE program anniversary *or* whose failure to renew is 12 or more months in the future; 1 if failure to renew is 11 months in the future; etc. to 12 if the person failed to renew in the month	0.737	2.40
FSTEXP	An interaction term for exposure and first-year enrollment (FSTYEAR * EXPOSURE)	1.39	2.96
FSTMTD	An interaction term for month-to-death and first-year enrollment (FSTYEAR * MTD)	0.36	1.82
FSTMTNR	An interaction term for month-to-nonrenewal and first-year enrollment (FSTYEAR * MTNR)	0.25	1.42
Other Explanatory Variables			
AGE	Age in years	76.0	7.33
MALE	A binary variable = 1 if enrollee is male; 0 otherwise	0.29	0.45
BLACK	A binary variable = 1 if enrollee is African American; 0 otherwise	0.06	0.24
NRSHOME	A binary variable = 1 if enrollee resides in a nursing home during the eligibility period; 0 otherwise	0.03	0.17
SINGLE	A binary variable = 1 if enrollee is single during the eligibility period; 0 otherwise	0.15	0.35

Continued

Table 1: Continued

Variable		*Mean*	*s.d.*
WIDOWED	A binary variable = 1 if enrollee is a widow in the eligibility period; 0 otherwise	0.52	0.50
DIED	A binary variable = 1 if enrollee died in the succeeding 12-month period; 0 otherwise	0.12	0.32
NONRENEW	A binary variable = 1 if enrollee failed to renew PACE membership in the succeeding 12-month period; 0 otherwise	0.1	0.31
REENROLL	A binary variable indicating reenrollment in PACE. REENROLL = 1 for persons with NONRENEW = 1 if subsequently reenrolled prior to July 1987; 0 otherwise	0.014	0.12
IN3TO6	A binary variable = 1 if prior year income was between \$3,001 and \$6,000; 0 otherwise	0.27	0.44
IN6TO9	A binary variable = 1 if prior year income was between \$6,001 and \$9,000; 0 otherwise	0.32	0.47
IN9TO12	A binary variable = 1 if prior year income was between \$9,001 and \$12,000; 0 otherwise	0.24	0.43
IN12TO15	A binary variable = 1 if prior year income was between \$12,001 and \$15,000; 0 otherwise	0.11	0.32

cate, respectively, whether the beneficiary filled any prescription in the month and, if so, how many.

The explanatory variables fall into three categories. First is a measure of calendar time (TIME). TIME simply dates the observation. If there is a secular trend toward higher drug use over time, as the U.S. Congressional Budget Office (1989) and others have argued, it will show up as a positive coefficient on the TIME variable.

The vector of variables related to the timing and duration of PACE enrollment includes counts of the number of months between the date of the observation and three key events: (1) the beneficiary's initial enrollment date (EXPOSURE), (2) the date of death (MTD), if the beneficiary died within 12 months of the observation (DIED), and (3) the last month of PACE entitlement (MTNR) for persons who dropped out of the program within 12 months of the observation (NONRENEW). A dummy variable (REENROLL) identifies beneficiaries who dropped out of PACE and subsequently reenrolled during the study period.

These are the principal behavioral-response variables in the model. We hypothesize a positive coefficient on EXPOSURE, which would indicate that program recipients' response to insurance coverage is not

instantaneous, but follows instead some defined time path. We expect a positive coefficient on the month-to-death variable, MTD, if prescription use follows patterns observed among other types of health services. On the other hand, we hypothesize negative signs on NONRENEW and MTNR on the presumption that persons most likely to drop out of the program are those who use it least.

The model also contains a set of terms that interact EXPOSURE, MTD, and MTNR with a dummy variable (FSTYEAR) identifying PACE beneficiaries who joined PACE in its first year of operation (July 1984 through June 1985). Given the unique conditions that accompany the inauguration of all new social programs, it is possible that early PACE entrants differ systematically in their prescription utilization patterns compared to later entrants. The coefficients on FSTYEAR and the three interaction terms (FSTEXP, FSTMTD, and FSTMTNR) serve to capture these potential differences.

Because there is no theory or prior literature to guide us in selecting a particular functional form for the dynamic variables in the model, we define both linear and nonparametric free-form specifications. In the linear versions of the model, TIME, EXPOSURE, MTD, and MTNR are entered as continuous variables as defined in Table 1. In the free-form versions, TIME is replaced by 35 dummies representing each calendar month except July 1984; EXPOSURE is replaced by 35 variables representing each exposure-month (excluding the second[11]) since initial enrollment; MTD is replaced by 12 dummies representing each month in the year leading to death (for decedents); and MTNR is similarly replaced by 12 dummies representing the months prior to nonrenewal (for dropouts). To keep the analysis within manageable bounds interaction terms (FSTEXP, FSTMTD, and FSTMTNR) are included only in the regressions with linear time effects.

The final set of variables in the utilization model are personal characteristics. We are limited here to information available on the annual PACE enrollment forms completed by each beneficiary. These variables include age (AGE), gender (MALE), race (BLACK), residential status (NRSHOME), marital status (SINGLE and WIDOWED), and four categorical income variables (INC3TO6, INC6TO9, INC9TO12, INC12TO15).

It is worth noting that this model contains no variable for prescription charges. This is appropriate, of course, because PACE beneficiaries face the same out-of-pocket expense for every prescription with a retail price equal to or above the program copayment amount. When the retail price falls below this level ($4.00 during the study period), beneficiaries are responsible for the entire amount and pharmacists receive no reim-

bursement from PACE. As a consequence, the PACE database contains few such claims.

DESCRIPTIVE RESULTS

The mean characteristics of the sample (see Table 1) closely match those of the PACE population as a whole. The typical enrollee is a widowed white female in her midseventies living in a private home with an annual income of between $6,000 and $9,000. Three percent of the enrollees are nursing home residents, a rate slightly below that for all aged Pennsylvanians. At any given point in time nearly 12 percent of PACE beneficiaries are within a year of death. An additional 11 percent will not renew their PACE membership for the following year. Of this latter group, slightly more than one in ten will renew (REENROLL) at a later date.

On any given month between July 1984 and June 1987 nearly two-thirds of all enrollees filled at least one prescription outside of the hospital (RXUSER). The average number of prescriptions filled by users (USERRATE) was three per month, yielding a mean utilization rate across the entire sample/time frame of 1.92 prescriptions per month.

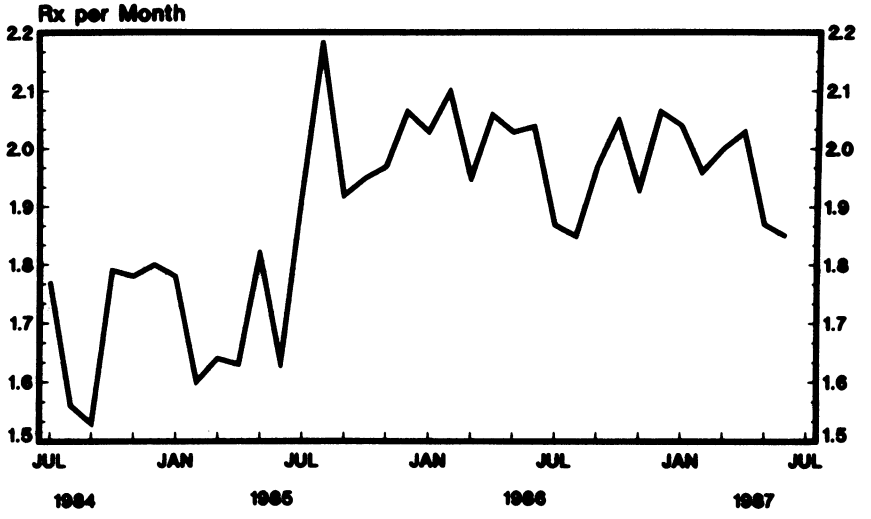
Figure 1 shows how actual monthly per capita utilization rates changed over the 36 months of the study. With the exception of the pronounced upward shift commencing in July 1985—a point we return to later—it is difficult to read any systematic trend in this time series. This is not surprising given the complex dynamic relationships at work here. Factors that may be expected to produce increasing levels of use (pharmacological advances and new drug therapies, population aging, beneficiary adaptation to insurance coverage, disenrollment of low users) are countered by factors having the opposite effect (enrollment growth representing new "inexperienced" beneficiaries and deaths among high users, to name just two).

MULTIVARIATE RESULTS

Our multivariate findings are described in the next three sections. We begin with a discussion of dynamic effects (linear and free-form) as that is the central focus of this article. A short section then describes differences in prescription utilization patterns according to the demographic characteristics of PACE beneficiaries.

None of the equations explained much of the total variation in prescription drug use. The highest R^2 achieved in any of the ordinary

Figure 1: PACE Utilization by Calendar Month



least squares (OLS) equations was 0.033.[12] Such low explanatory power is typical of multivariate analyses of health services use at the individual level (Newhouse et al. 1989). It does not appear to be due to the fact that the unit of analysis is the month as opposed to the year—a more typical time frame for utilization studies. In previous work we have found little difference in overall predictive power whether drug utilization models are estimated with annual, quarterly, or monthly prescription rates (Stuart et al. 1989, 1991). The likely reason is the relatively high degree of persistence in drug purchases over even short periods of time.

LINEAR TIME EFFECTS

Findings from the linear time-effects regressions are presented in Tables 2 and 3. Table 2 reports parameter coefficients from the logit equation for probability of use (column 1) and the semi-log equation for level of use by users (column 2).[13] The output from these regressions is used to produce, via equation (6), the predicted marginal effects shown in Table 3. The first column in Table 3 shows the predicted contribution to monthly prescription claims volume attributable to changes in the probability of drug use, $[\beta_j/(1 + \exp(X\beta)][E(Y)]$; column 2 shows the contribution to Rx use of changes in the level of use by users, $[\gamma_j + \delta_j X_j]\ [E(Y)]$; and column 3 shows the combined effect of changes in both the probability and level of use, $\{[\beta_j/(1 + \exp(X\beta)\ )$

Table 2: Parameter Estimates from Linear Time-Effects Regressions

Explanatory Factors†	*Probability of Use per Enrollee (RXUSER)*‡	*Level of Use per User in Logarithms (USERRATE)*§
TIME	-0.004*	-0.002*
	(11.5)	(2.72)
EXPOSURE	0.018*	0.004*
	(124.3)	(5.87)
MTD	-0.02	0.02*
	(3.2)	(4.52)
MTNR	-0.04*	0.01
	(12.4)	(0.42)
FSTYEAR	-0.48*	-0.03
	(41.3)	(0.87)
FSTEXP	0.05*	-0.002
	(36.8)	(0.71)
FSTMTD	-0.01	-0.01*
	(0.6)	(2.46)
FSTMTNR	-0.08*	-0.003
	(45.3)	(0.41)
AGE	0.01*	-0.001
	(30.0)	(1.61)
MALE	-0.18*	-0.02
	(32.3)	(1.93)
BLACK	-0.05	-0.03
	(0.7)	(1.44)
NRSHOME	0.05	0.28*
	(0.4)	(8.85)
SINGLE	0.08	0.03
	(2.9)	(1.79)
WIDOWED	0.17*	0.05*
	(21.1)	(3.39)
DIED	0.55*	0.16*
	(30.8)	(4.53)
NONRENEW	-0.65*	-0.006
	(51.2)	(0.13)
IN3TO6	-0.07	-0.06*
	(1.1)	(2.35)
IN6TO9	0.05	-0.04
	(0.7)	(1.53)
IN9TO12	0.19*	-0.003
	(9.0)	(0.12)

Continued

Table 2: Continued

Explanatory Factors†	*Probability of Use per Enrollee (RXUSER)*‡	*Level of Use per User in Logarithms (USERRATE)*§
IN12TO15	0.37*	-0.04
	(27.3)	(1.24)
REENROLL	-0.16	-0.03
	(2.1)	(0.81)
INTERCEPT	0.31	0.93*
	(3.2)	(13.8)
N	27,301	17,456
R^2		.032

*Significant at $p < .01$ in a two-tailed test.

†Reference categories are: persons enrolling in PACE after June 30, 1985; female; non-African American; community dwelling; married; survivor; continuously enrolled; and annual income below $3,000.

‡Chi-squared statistics in parentheses.

§White (1980) absolute *t*-ratios in parentheses.

$+ \gamma_j + \delta_j X_j]\}[E(Y)]$. These marginal effects are computed in relation to a benchmark case with the following characteristics: a non-African American married female, age 78, living in the community, with an annual income below $3,000, who enrolled in PACE after June 1985 and was continuously enrolled through June 1987. The TIME and EXPOSURE benchmarks were set at December 1985 and 12 months, respectively.

The findings for the four continuous time variables (EXPOSURE, MTF, MTD, and TIME) tell an interesting story. The most unexpected result is the negative and statistically significant coefficients on the calendar time variable (TIME). We estimate that, holding other factors constant, the number of PACE claims fell by an average of .0091 per month (Table 3, column 3) over the three years of the study. This may seem to be an unimportant rate of decline. However, in cumulative terms it represents a 17 percent reduction in *Rx* claims filed per PACE beneficiary between July 1984 and June 1987. We estimate that about half of the decline attributable to TIME is due to a reduced probability of use (-.0048 claims per month) and half to reduced levels of use by users (-.0043 claims per month).

Countering this secular reduction in *Rx* use is the program response associated with longevity on PACE (EXPOSURE). The EXPOSURE

Table 3: Predicted Marginal Effects of Model Variables on Monthly Prescription Utilization Rates of PACE Enrollees by Source of Response

*Explanatory Factors**	*Contribution Due to Change in Probability of Use* $\{\beta_j/[1+\exp(X\beta)]\}[E(Y)]$	*Contribution Due to Change in Level of Use by Users* $[\gamma_j+\delta_j X_j][E(Y)]$	*Contribution Due to Change in Both the Probability and Level of Use* $\{\beta_j/[1+\exp(X\beta)] + \gamma_j+\delta_j X_j\}[E(Y)]$
	(1)	*(2)*	*(3)*
TIME	-0.0048	-0.0043	-0.0091
EXPOSURE	0.0119	0.0076	0.0194
MTD	-0.0144	0.0383	0.0239
MTNR	-0.0273	0.0151	-0.0123
FSTYEAR	-0.3074	-0.0479	-0.3552
FSTEXP	0.0315	-0.0042	0.0273
FSTMTD	-0.0050	-0.0182	-0.0232
FSTMTNR	-0.0539	-0.0050	-0.0589
AGE	0.0070	-0.0029	0.0041
MALE	-0.1773	-0.0453	-0.1626
BLACK	-0.0292	-0.0579	-0.0871
NRSHOME	0.0314	0.5172	0.5486
SINGLE	0.0491	0.0591	0.1083
WIDOWED	0.1121	0.0927	0.2048
DIED	0.3565	0.3025	0.6590
NONRENEW	-0.4170	-0.0112	-0.4283
IN3TO6	-0.0426	-0.1075	-0.1501
IN6TO9	0.0332	-0.0683	-0.0351
IN9TO12	0.1201	-0.0056	0.1145
IN12TO15	0.2425	-0.0657	0.1768
REENROLL	-0.1066	-0.0635	-0.1702

*Benchmark case: TIME = December 1985, EXPOSURE = 12 months, MTD = 0, MTNR = 0, AGE = 78, persons enrolling in PACE after June 1985, female, non-African American, community dwelling, married, survivor, continuously enrolled, and annual income below $3,000.

coefficient is positive and significant in both the RXUSER and USERRATE equations—indeed, it is the most highly significant explanatory variable in either model. All else being equal, PACE beneficiaries filled .0194 more prescriptions per month of enrollment during the study period. About 60 percent of this response is due to increased probability of use (.0119 claims per month) and 40 percent (.0076 claims per month) to more claims filed by users.

The month-to-death and month-to-nonrenewal effects must be

interpreted in concert with the two dummy variables, DIED and NONRENEW. The coefficients on the binary variable, DIED, are positive, highly significant ($p < .0001$), and quite large in both the probability and level-of-use models. The marginal effect on prescription use of being in the final year of life is .659 *Rx* claims per month—34 percent above mean utilization rates for the PACE sample as a whole—of which .3565 claims (54 percent) is due to higher probability of use, and .3025 claims (46 percent) is due to higher levels of use by users. From this plateau, the probability of use appears to decline slightly in the final months of life as seen in the negative coefficient for the MTD variable in the RXUSER equation, albeit the effect is not statistically significant.[14] Among prescription users the marginal effect of moving one month closer to death is .0383; about half a prescription difference over the final year of life.

The coefficients on the binary "nonrenewer" (NONRENEW) and continuous month-to-nonrenewal (MTNR) variables suggest that an individual's decision to leave PACE follows a pattern of declining utilization rates relative to other beneficiaries.[15] Even before they begin their last year in the PACE program, future dropouts fill about 22 percent fewer prescriptions per month on average (the marginal contribution of NONRENEW is -.4283 claims per month). During that final year, the probability of use declines significantly (the marginal effect is -.0273 scripts per month). The rate of use by future dropouts who fill one or more prescriptions in a month is not statistically different from the rest of the PACE population. The small numbers of PACE beneficiaries who drop out and then reenroll (REENROLL) appear to have lower-than-average rates of drug use, but here too the results are not statistically significant.

The coefficients on the dummy variable FSTYEAR and the three time-interaction effect variables (FSTEXP, FSTMTD, and FSTMTNR) provide strong evidence that the behavior of persons who joined PACE in the initial year of program operation (July 1984–June 1985) differed significantly from that of later entrants. As can be seen in Table 2, only one of the eight coefficients on these four variables is positive (the exposure response of first year entrants—FSTEXP). All the rest point to drug use that is lower than average by members of this cohort. (The marginal effects on these variables, shown in Table 3, suggest that most of the difference is due to lower than average probabilities of use.) It would thus appear that the program benefited from a form of "favorable selection" during its maiden year.

This selection phenomenon also helps explain the sharp jump in PACE utilization rates in July 1985 noted earlier (see Figure 1). An

increase in average utilization need not mean that everyone is using more; the same result will occur if below-average users and nonusers are disproportionately represented among program dropouts. The negative signs and large coefficients on the FSTYEAR and FSTMTNR variables suggest that this may be what happened. On July 1, 1985, PACE eligibility ended for 36,512 first-year enrollees who failed to renew their membership applications for 1985/1986 (Pennsylvania Department of Aging 1990). Their departure left an enrollment pool populated with relatively higher users. This effect was then augmented by the fact that persons enrolling in PACE after July 1985 were themselves higher users.

FREE-FORM TIME EFFECTS

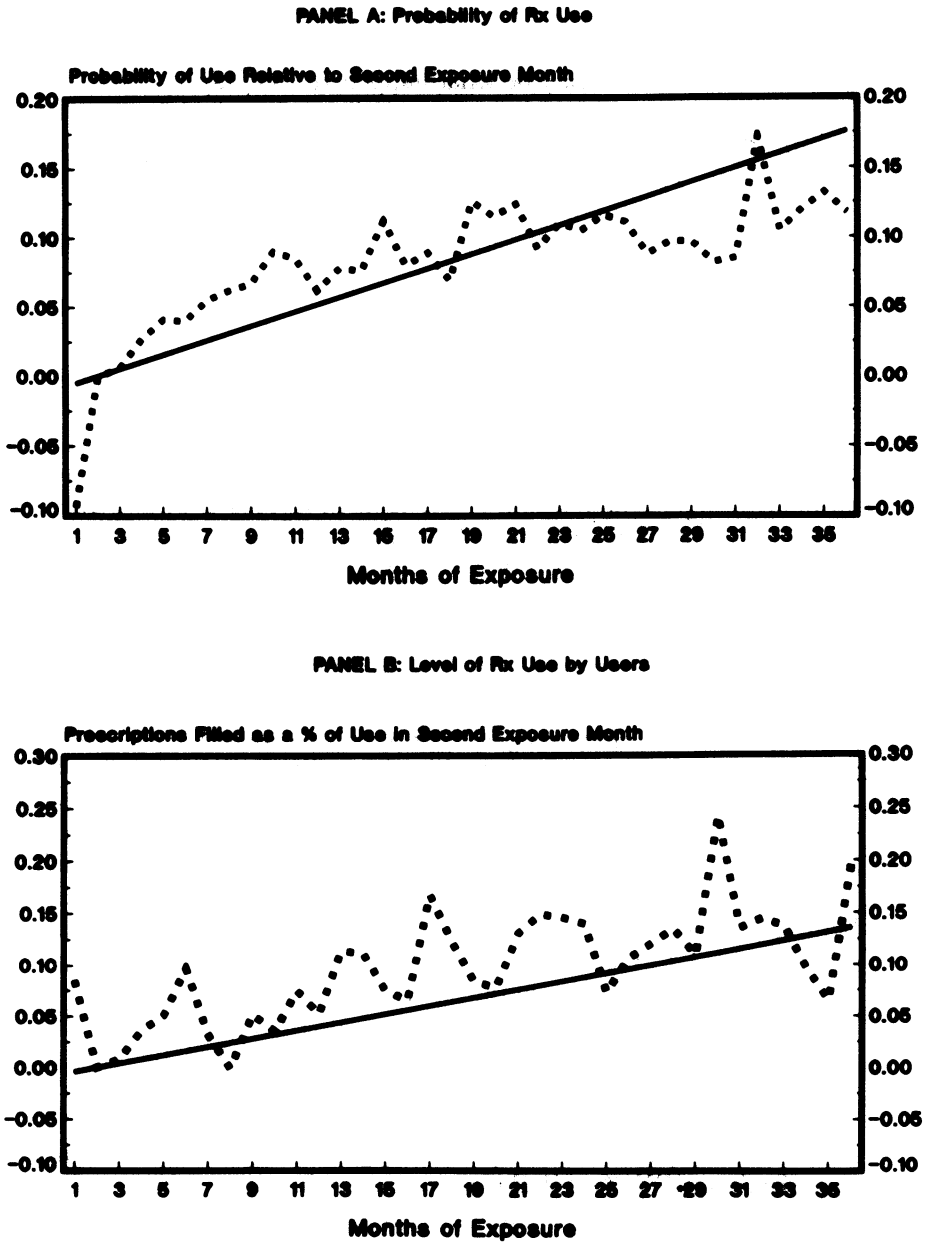
The free-form time effects models provide a more detailed picture of changes in drug use with program exposure, progression to death, and time to nonrenewal. Rather than report the entire output from these estimates, we plot the relevant coefficients in figures 2, 3, and 4.[16] The coefficients from the linear probability and level-of-use equations (Table 2) are shown as solid lines in Panel A and Panel B, respectively, in each figure. The dashed lines show the dummy coefficients by month in the free-form version of the same model.

The exposure-response (EXPOSURE) results are plotted in Figure 2. The vertical axis in each panel measures the estimated percentage difference in prescription use between a given exposure-month and the reference period (the second month of enrollment), holding all other factors constant. For example, the free-form specification of EXPOSURE in the probability-of-use equation (the dashed line in Panel A) indicates that enrollees were 10 percent less likely to fill a prescription in their first month of PACE coverage than in their second month, all else being equal. This compares with an estimated difference of less than 1 percent with EXPOSURE specified in linear form (the solid line).

In all, 56 of the 70 exposure-month dummies plotted in Figure 2 reached conventional levels of statistical significance: 31 in the RXUSER equation, 25 in the USERRATE equation. The nonsignificant variables clustered near the reference month, which is what one would expect given the short time interval between exposure-months.

Visual inspection of the plots in Figure 2 suggests that the linear specification of EXPOSURE may conceal an important characteristic in beneficiaries' response to PACE coverage. The dummy coefficients in the probability-of-use equation (Panel A) rise sharply, then appear to level off. Over the first ten months of exposure the mean probability that

Figure 2: PACE Utilization by Month of Exposure



a beneficiary will fill any prescription increases by 20 percentage points; over the next 26 months the probability increases by approximately five additional percentage points.

No such pattern is evident in the level-of-use dummies plotted in Panel B. While some of the month-to-month variability in this series is surely due to random error (10 of the 35 dummy coefficients were insignificant at the .05 level), a standard *F*-test indicates that the free-form specification fits the data significantly better than does the linear specification.

Figure 3 is a chart of the effect of impending death on prescription use rates. The free-form estimates in the two regressions shown here are produced by adding the parameter coefficient for the binary variable DIED, in the original equation, to each of the 12 dummy variables representing months to death. By so doing, we estimate the marginal effect of an additional month toward death given that the person will die within 12 months. Ten of the 12 dummies for month to death are significant in the probability-of-use equation (Panel A); all 12 are significant in the level-of-use regression (Panel B).

Here, too, one can see the additional information gained from the free-form specification. The large drop in probability of use in the death month (month 0) was expected since many elderly die in hospitals where their drug usage is covered by Medicare rather than PACE. Removing this effect from the time series leaves a flat profile of probability of use in the last year of life. The linear and free-form level-of-use coefficients in Panel B show basically similar patterns of change as death approaches, albeit the last five dummy coefficients (months 4 to 0) suggest a rising rate of prescription use during this phase of life. On grounds of goodness of fit, the dummy specification is preferred.

Figure 4 portrays the results of the month-to-nonrenewal variable. The plots for the free-form specification were produced by adding the coefficient of the shift variable, NONRENEW, to each of the dummy coefficients for month to nonrenewal. The interpretation is analogous to the month-to-death results previously described.

All 12 dummies in the RXUSER equation (Panel A of Figure 4) were negative and significant, confirming the linear pattern of declining probability of use in the final year of enrollment. By contrast, only two dummies (months 11 and 0) were significant in the USERRATE equation (Panel B). In other words, persons who fail to renew their membership but continue to have prescriptions filled are indistinguishable from beneficiaries who remain continuously enrolled. The markedly different patterns in probability and level of use found here (and in the previous

Figure 3: PACE Utilization in the Final Year of Life

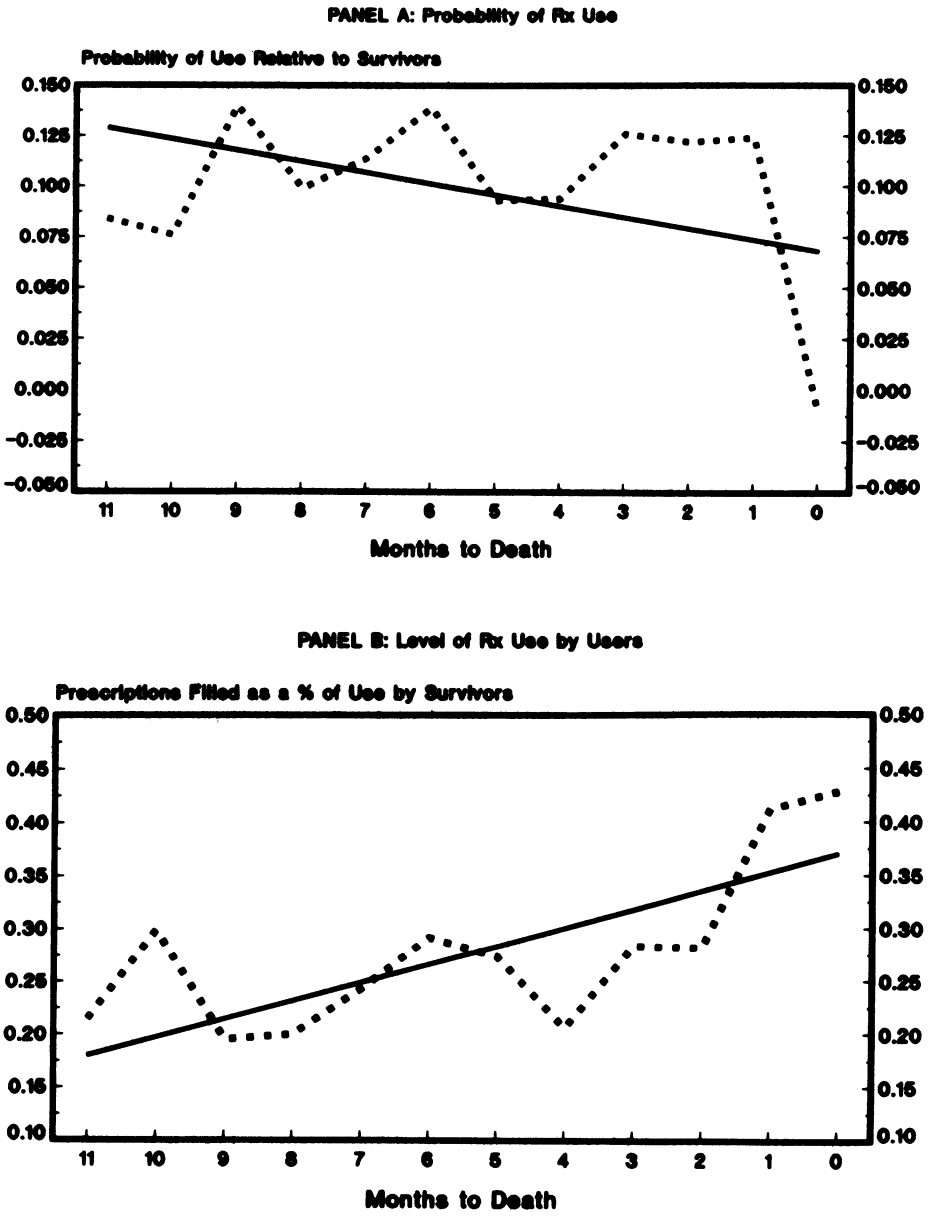
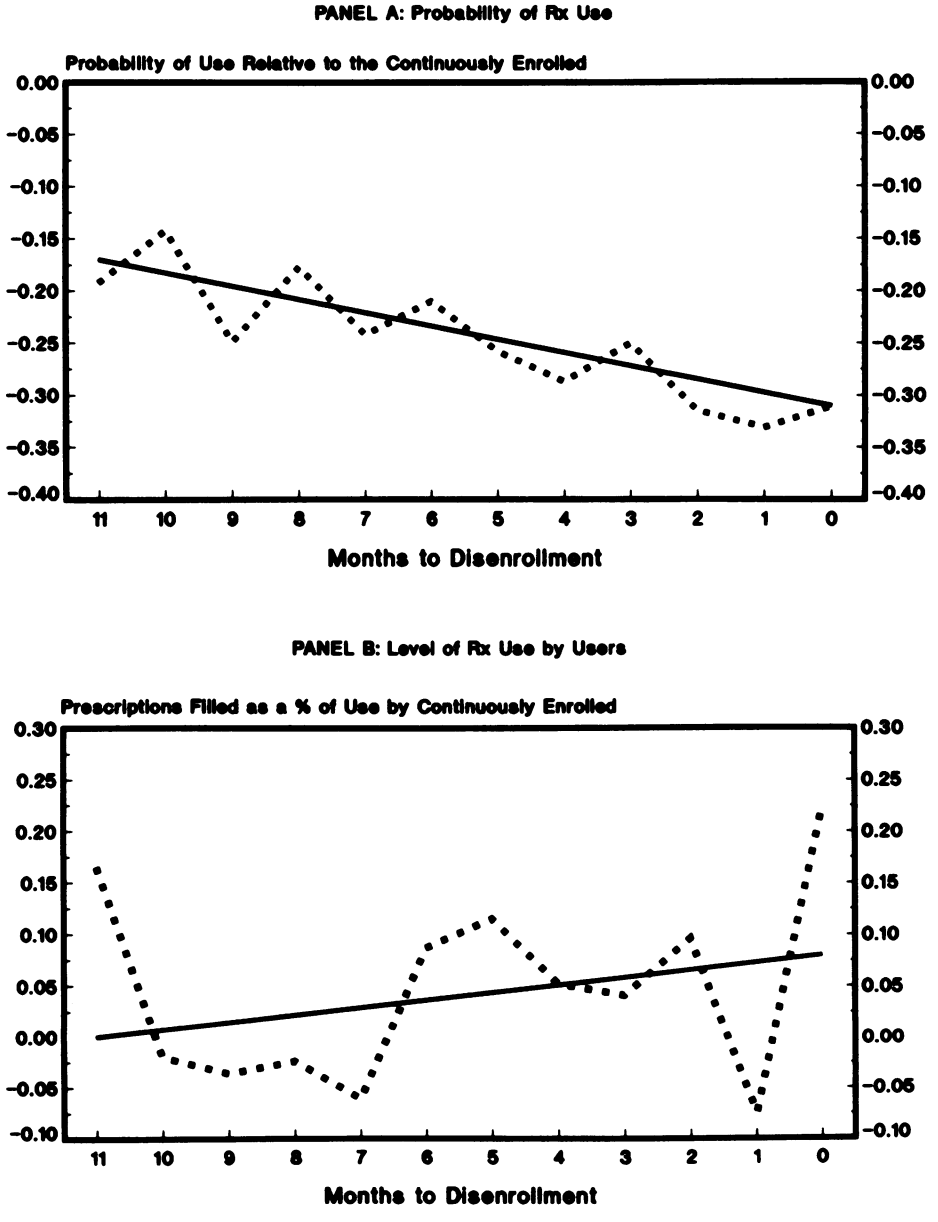


Figure 4: PACE Utilization in the Final Months of Enrollment



regressions as well) show why the two-stage estimation procedure is preferred over a single utilization equation.

We did not plot parameter coefficients for calendar time since fewer than half of the free-form dummy TIME coefficients were statistically significant. Nonetheless, the signs are consistent with the negative secular time trend found in the linear models.

DEMOGRAPHIC FACTORS AND PRESCRIPTION DRUG USE

Although the emphasis of this article is on dynamic effects, it is worth noting that the relationship of demographics to prescription drug use among PACE enrollees is consistent with other published work in the field (LaVange and Silverman 1987; Moeller and Mathiowetz 1989; Pulliam, Hanlon, and Moore 1988; U.S. Congress 1987). As can be seen in Table 3, prescription utilization rises with age (AGE), but the effect is driven wholly by higher probabilities of use (indeed, age contributes negatively to the level of use by users). Both the probability and level of prescription utilization are lower for males and African American beneficiaries. Somewhat surprisingly, nursing home residents are no more likely to fill a prescription in a given month than are other beneficiaries. But among those who do fill at least one prescription, residence in a nursing home contributes over half a prescription a month in predicted utilization. Prescription use also varies by marital status. Both single and widowed beneficiaries have higher utilization rates than do married persons, but only in the latter case is the effect statistically significant. Widowhood contributes two-tenths of a prescription to monthly utilization rates, half coming from a higher probability of use (.1121 claims per month) and half from higher utilization rates by users (.0927 claims per month).

DISCUSSION

Taken as a whole, these results provide a much richer picture of prescription drug utilization patterns for an elderly population than could be obtained from standard cross-sectional analysis. But as is often the case, research findings raise as many questions as they answer. In this section we discuss the implications of certain results and set some directions for future research.

The findings regarding the pure time trend in outpatient prescription drug use were a surprise. Conventional wisdom holds that prescription expenditures are rising among all classes within the population,

most notably the aged. Although our study does not address changes in prescription prices, we found no evidence that expenditure growth is being fueled by increasing rates of drug utilization. Indeed, based on our linear estimates, PACE enrollees filled approximately 17 percent fewer prescriptions in June 1987 than in July 1984, after other factors are taken into account. The usual caveats apply. Because our sample was limited to one state and a three-year period, we may have missed developments that occurred elsewhere or happened at other times.

We stress that this finding does not imply that PACE utilization rates or program expenditures actually declined. The increase in utilization associated with beneficiaries' exposure response to PACE more than offset the declining secular trend in drug use over the three years of the study. Program expenditures rose both for this reason and because retail prescription drug prices increased 28 percent between 1984 and 1987 (U.S. Department of Commerce 1990).

There is also a question of semantics: What constitutes secular change in drug utilization? Our approach was to specify a calendar time variable that, given the other dynamic variables in the model, captured any residual temporal change in per capita use of all types of prescription drugs combined. A more fruitful approach might be to focus on specific classes of drugs. It can easily be shown statistically that, unless temporal changes in drug use are highly correlated across therapeutic classes, no trends will be apparent in overall utilization rates. Prescription claims databases like that maintained by the PACE program represent a potentially valuable resource for this type of study.

The enrollment duration results provide convincing evidence of a strong and positive exposure response among PACE beneficiaries unrelated to population aging or other time-related variables included in the study. However, the driving force behind this response is far from clear. The large jump in the probability of drug use in the first half-year of enrollment might well signal a program learning phase as new beneficiaries (and their prescribers) adjust to the insurance coverage provided by PACE. Unfortunately, our data set contains no observations on drug use for beneficiaries *before* they joined PACE and, therefore, we cannot directly test the hypothesis that the presence of third-party coverage induces greater utilization. The fact that some beneficiaries had private prescription drug coverage prior to—and after—their enrollment in PACE (Ahern et al. 1989) makes interpretation that much more uncertain. And even if the first few exposure-month results do reflect induced demand, is it reasonable to believe that the insurance adjustment process would last for a whole three years? In short, there is much left to explain on this score.

The same can be said about the evidence of selection effects in program enrollment. It was impossible to test directly for selection bias in the PACE enrollment decision because we lacked drug use data for PACE-eligible individuals who chose *not* to enroll. The month-to-nonrenewal results indicate that beneficiaries who choose to drop PACE have lower propensities to consume prescription drugs than those who remain enrolled. But can one draw any inference about the utilization behavior of those who failed to select PACE in the first place? In other words, are selection and "deselection" symmetric phenomena?

While we cannot answer that question directly, the findings related to the behavior of first-year entrants provide additional information about the selection process. Every voluntary social service program "suffers" adverse selection in the sense that people who need the benefits most are the most likely to enroll (and remain enrolled). We wished to determine whether the degree of selection bias remains constant over time. The finding that the first cohort of PACE enrollees had systematically lower utilization rates is an indicator of "favorable" selection—at least in relative terms. Why this occurred requires further study. One plausible explanation lies in the intensive marketing campaign conducted by the Commonwealth of Pennsylvania in preparation for the inauguration of PACE in July 1984. Designed to inform the elderly about the new prescription drug program, it may also have induced a greater number of healthy persons to sign up for PACE benefits than later marketing efforts did.

Interpretation of the results concerning the last year of life is straightforward. It has long been known that the use of hospital and physician services rises rapidly in the period just before death. Why should prescription drugs be any different? But there are differences. According to 1976 HCFA data, nearly half of all the Medicare expenses incurred by decedents in their last year of life are spent within 60 days of death; just 6 percent are spent in the 60 days that initiate the last year of life (Lubitz and Prihoda 1984). Our findings indicate that the rise in prescription drug use in the final months of life is much more gradual than this. By deduction, we also know that the point in time when death begins to (ex post) predict higher drug use is more than 12 months prior to the death date. Additional analysis is necessary to determine how long this period might be.

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NOTES

1. The other states are New Jersey, New York, Maryland, Maine, Rhode Island, Connecticut, Delaware, Illinois, and Vermont.
2. Beginning in 1990, PACE instituted a biennial enrollment period for the lowest income beneficiaries.
3. Strictly speaking, the interval cross-section is representative of the population unweighted by length of enrollment (just as is the case in ordinary cross-sections). From the perspective of the population's total enrollment duration, this sample selection procedure underrepresents PACE beneficiaries with long enrollment periods and overrepresents those with short histories. However, this has no effect on the properties of regression estimates based on such samples as long as program exposure is included as a conditioning variable.
4. Another way to view the interval design is as a panel data set stripped of person-specific effects over time. These individual effects are typically of minimal empirical interest in and of themselves. Removing them improves data tractability while preserving the sample variability which is of most interest.
5. We tracked PACE enrollment and survival status for one year beyond June 1987 in order to capture the effects of impending death and disenrollments on prior utilization behavior over a full three-year period.
6. For ease of exposition we employ the term "user" to designate beneficiaries who fill one or more prescriptions in a month. Whether users actually take their medicine as prescribed cannot be determined from the data set.
7. RESET tests for misspecification (Ramsey and Schmidt 1976) on the second-stage equation reveal no manifest misspecification of the model, which we thus take as a tentatively adequate representation of the data generation process (see also footnote 13).
8. The assumption of normality appears justified; the test statistic was well under the standard critical values in each case.
9. See footnote 13.
10. The variance regression excluded those variables that were observed from preliminary runs to have no effect on the squared residuals. The excluded variables were TIME, SINGLE, FSTYEAR, the income groups, FAIL, and REENROLL. Variable definitions are given in the next section.
11. We chose the second rather than the first exposure month as the excluded

category. Observations for the number of prescription claims filed in the initial enrollment month and last month of life were adjusted to correct for the fact that the average PACE enrollee was covered for less than a complete month in these instances.

12. There is no coefficient of determination for the logit estimator.
13. Note that the *t*-ratios in the USERRATE equation have been corrected for heteroskedasticity. Tests by White (1980) for the existence of heteroskedasticity in this equation resulted in a rejection of the null of a constant variance. Following White, we computed a heteroskedastic-consistent estimate of the covariance matrix and derived asymptotic *t*-ratios from it.
14. The decline may be due to the fact that the individuals in their final year of life are more likely to be hospitalized, in which case drug therapy is paid for by Medicare rather than PACE.
15. We considered the hypothesis that variables relating to disenrollment and reenrollment were simultaneously determined with prescription use (e.g., low use in the months prior to the PACE reapplication date causes disenrollment). Hausman (1978) tests of simultaneous equations bias failed to reject the null of exogeneity. Probability values were all in excess of 20 percent.
16. It is worth noting that the parameter coefficients for the 11 demographic variables in the time-continuous and time-dummied versions are virtually identical, indicating that the estimates are not sensitive to model specification.

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