

**THE DISTRIBUTION OF PRESCRIPTION DRUG USE BY THE ELDERLY  
- THE PACE EXPERIENCE**

Arnold F. Shapiro, Bruce C. Stuart, N. Edward Coulson & John T. Monyak

Penn State University

**ABSTRACT**

This study examines four and-a-half years of prescription records for a population of elderly Pennsylvanians who have relatively comprehensive out-of-hospital drug coverage under the Pharmaceutical Assistance Contract for the Elderly (PACE) program.

The paper begins with a brief overview and history of the PACE program. This is followed by a discussion of the sampling design and the demographic parameters. Mean PACE utilization and expense rates are then considered. Given this background, the discussion turns to the determination of nonparametric estimations of the distributions.

# THE DISTRIBUTION OF PRESCRIPTION DRUG USE BY THE ELDERLY - THE PACE EXPERIENCE<sup>1</sup>

Arnold F. Shapiro, Bruce C. Stuart, N. Edward Coulson & John T. Monyak

## INTRODUCTION

This study examines four and-a-half years of prescription records for a population of elderly Pennsylvanians who have relatively comprehensive out-of-hospital drug coverage under the Pharmaceutical Assistance Contract for the Elderly (PACE) program. The objective is to investigate the temporal nature of drug use and expense patterns for the elderly.

The paper begins with a brief overview and history of the PACE program. This is followed by a discussion of the sampling design and the demographic parameters. Mean PACE utilization and expense rates are then considered. Given this background, the discussion turns to the determination of nonparametric estimations of the distributions. The paper concludes with a comment on the implications and limitations of the study and anticipated future research.

---

<sup>1</sup>The results reported here were made possible by the efforts of a group of investigators (D. Lago, M. Smoyer, and F. Ahern) at The Penn State University in collaboration with the Pennsylvania Department of Aging (PDA) [L. Rhodes, Secretary, T. Snedden, Director and Terri Brown, Research & Evaluation Chief, Bureau of Pharmaceutical Assistance (PACE)]. The extensive and expert guidance of Y. M. Zubovic and the invaluable computer expertise and assistance of V. X. Rabatin are also acknowledged.

## THE PACE PROGRAM

The PACE program was inaugurated on July 1, 1984 to provide help to elderly Pennsylvanians in paying for out-of-hospital prescription drugs. PACE is administered by the Pennsylvania Department of Aging and is financed by dedicated revenues from the state's lottery. Eligibility is limited to state residents age 65 and older with annual incomes under \$12,000 if single and \$15,000 if married. Smyer et. al. (1986) have estimated that 45 to 55 per cent of elderly Pennsylvanians meet these criteria. Somewhat more than half of those eligible for benefits apply for and receive PACE coverage. PACE enrollment was approximately 435,000 as of September 15, 1989.

PACE provides broad and comprehensive outpatient coverage of prescription drugs, insulin and insulin syringes. It also provides drug coverage for eligible nursing home residents, but given the small numbers involved (about four percent of total enrollees) PACE remains basically an outpatient drug program, and will be referred to as such throughout this article. Experimental drugs, "DESI" drugs,<sup>2</sup> medical supplies other than syringes, and non-prescription medications are not covered. For medications provided in tablet or capsule form, dosages are limited to the lesser of a 30 days supply or 100 units per claim. The PACE cardholder is required to pay a flat copayment of \$4.00 for each prescription received regardless of price. This copayment amount has remained unchanged since 1984. Because retail drug prices have risen sharply in the last few years, beneficiaries now contribute a significantly lower percentage of prescription charges than when the

---

<sup>2</sup>"DESI" (Drug Efficacy Study Implementation) drugs are those products introduced between 1928 and 1962 and considered less than effective by the FDA.

program began.

The PACE program pays for drugs provided by community pharmacies, hospital outpatient pharmacies, mail order houses, and dispensing physicians. Reimbursement for participating pharmacies is equal to the lesser of their usual and customary charge or the average wholesale price plus a dispensing fee of \$2.75, less the copayment amount. Dispensing physicians are subject to the same payment limits, but are not paid a dispensing fee.

### METHODOLOGY AND DEMOGRAPHIC PARAMETERS

The study design involved profiling prescription drug utilization and expense patterns for PACE beneficiaries over the period July 1, 1984 through December 31, 1988. All beneficiaries who met the following criteria were included in the profiles: (1) initial enrollment date between July 1, 1984 through December 31, 1987; (2) known enrollment dates and valid Social Security numbers;<sup>3</sup> (3) at least one year of program exposure for survivors<sup>4</sup> (decedents were included regardless of period of exposure); and (4) no gap in PACE enrollment greater than 30 days.<sup>5</sup> The total number of persons meeting these criteria was 513,689 or approximately 88 percent of all PACE beneficiaries who enrolled

---

<sup>3</sup>A total of 11,777 individuals had unusable records. These included persons with missing initial enrollment dates (3,404), overlapping re-enrollment periods (1,641) and incorrect Social Security numbers (6,732).

<sup>4</sup>There were 24,654 non-decedents with less than one full year of PACE enrollment. For the most part, these are individuals who voluntarily failed to re-enroll in PACE on their first opportunity, but a small number were canceled either because of enrollment in MEDICAID or because of audits showing income above PACE guidelines.

<sup>5</sup>Persons with enrollment gaps of less than 30 days were assumed to be continuously enrolled.

during the study time frame.

The demographic characteristics of this sample are shown in Table 1 together with breakdowns by cohort and exposure year (explained below). Information on gender, age, and residential status was obtained from PACE cardholder files. These files contain data from the initial application and all annual re-enrollment forms that PACE beneficiaries are required to complete. The nursing home residents listed in Table 1 represent PACE beneficiaries who report being in a nursing home at the time of the initial PACE application and **all** subsequent re-enrollment applications.<sup>6</sup> The mortality data shown in Table 1 were determined by linking PACE enrollment history files with mortality data provided by the Pennsylvania Department of Health and the Health Care Financing Administration.<sup>7</sup>

---

<sup>6</sup>This rather restrictive definition of "continuously enrolled" nursing home resident was chosen to minimize the likelihood that individuals who spent only part of an exposure year in a nursing care facility would be included in the nursing home category. It should be noted that the PACE application forms provided only indirect evidence of residential status of PACE beneficiaries. Because changes in a beneficiary's residential status do not necessarily coincide with application dates, an individual may be listed as a nursing home resident, but spend part of the year in a private residence. According to data for the PACE cardholder files, a total of 22,246 individuals or 4.3 percent of the entire sample were nursing home residents at some point between July 1, 1984 and December 31, 1988. Of that number, 13,966 (63 percent) met the above definition for continuously enrolled nursing home residents.

<sup>7</sup>Compared to the general population of elderly in the Commonwealth of Pennsylvania, PACE beneficiaries tend to be older and are more likely to be female or widowed. Age and gender specific mortality rates among beneficiaries are significantly higher than for other Pennsylvanians. Because of the income restriction placed on PACE eligibility, beneficiaries are obviously less well to do than the average older person in the Commonwealth. However, the income distribution of PACE enrollees appears to be broadly representative of the subset of elderly with annual incomes below \$15,000.

**TABLE 1**  
**NUMBER OF PACE BENEFICIARIES BY DEMOGRAPHIC CHARACTERISTIC**  
**(000 OMITTED)**

Cohort Exposure Year	1984				1985			1986		1987
	1	2	3	4	1	2	3	1	2	1
<b>Category</b>										
Total	262	232	208	188	127	109	95	66	55	59
<b>Gender</b>										
Male	65	56	48	42	44	36	30	21	17	18
Female	197	177	160	146	83	73	65	45	38	40
<b>Age</b>										
65-69	57	53	49	46	41	36	32	27	24	26
70-74	70	65	60	55	33	29	26	14	12	11
75-79	62	55	50	45	26	23	20	11	9	9
80-84	42	36	31	27	16	13	11	7	6	6
85+	31	24	19	15	11	9	7	7	5	6
<b>Residence</b>										
Noninstitutional	257	230	207	186	123	107	94	63	54	56
Nursing Home	4	2	1	1	4	2	1	3	2	3
<b>Mortality Status</b>										
Survivor	246	217	195	176	118	102	89	61	52	55
Decedent	17	16	14	12	9	7	6	5	4	4

The classification of the sample into cohorts and years of exposure reflects the view that time can affect drug use and expense patterns in two distinct ways. If secular events, such as new pharmacological advances or environmental factors, influence utilization behavior, the impact should be evident in the claims experience of beneficiaries during the same span of calendar time regardless of when the beneficiaries actually joined the program. To see whether there are such calendar-related effects, all beneficiaries were assigned to

one of four calendar year cohorts (1984 to 1987) based on their initial enrollment dates.<sup>8</sup>

The dynamic effects of exposure to PACE benefit coverage on drug use patterns is captured by elapsed time beginning with the beneficiary's initial enrollment date and extending forward. Exposure periods are thus beneficiary-specific. For example, an individual who enrolled in PACE on August 16, 1984, would be assigned to the 1984 cohort and would have a first year of exposure which extended from August 16, 1984 through August 15, 1985. In contrast, an individual who enrolled in PACE on December 15, 1984, who also would be assigned to the 1984 cohort, would have a first year of exposure which extended from December 15, 1984 through December 14, 1985. Two operational measures of elapsed time were chosen: the exposure-year just described; and the exposure-quarter (three month intervals of elapsed time). Table 1 shows the disposition of the sample by exposure-year.<sup>9</sup>

To maintain a consistent measure of exposure, it was necessary to monitor the enrollment status of beneficiaries during each successive exposure period. The three possible status situations are: (1) the individual remained PACE enrolled throughout the exposure period, (2) the individual survived during the exposure period, but did not remain

---

<sup>8</sup>For example, persons enrolling for the first time between July 1, 1984 and December 31, 1984 are assigned to the "1984 cohort", persons enrolling for the first time in calendar 1985 are assigned to the "1985 cohort," and so on.

<sup>9</sup>In reading across this table, it is important to note that individuals are classed according to their demographic characteristics upon *initial* enrollment. Thus, for example, beneficiaries in the 1984 cohort who were between 65 and 69 years of age upon enrollment are assigned to the "65 to 69" age group. The experience of this specific group of persons is tracked over time and reported under the "1984 cohort, age 65 to 69" heading in tables with age breakdowns. This convention was adopted so that the impact of selection could be traced.

Changes in chronological age are not lost in this reporting process. Given the definition of exposure, all persons age exactly one year from exposure year to exposure year.

PACE enrolled for the entire period, and (3) the person died at some point during the exposure period. The second status situation proved problematic because there was no way to determine when PACE eligibility effectively ends for persons who voluntarily fail to re-apply for PACE coverage.<sup>10</sup> Between two and six percent of the survivors in the sample failed to re-enroll at the end of each exposure-year. Rather than devise some arbitrary method of extrapolating utilization rates for these few exposures, they were excluded from the tabulations.<sup>11</sup>

The analysis of the PACE claims files was limited to two measures of program outcomes: (1) the number of prescriptions filled and/or refilled by sampled beneficiaries during each exposure period aggregated according to date of service; and (2) the annual (or quarterly) expense for these products. "Expense" is defined in terms of the usual and customary charges submitted by participating pharmacies, not the amount actually paid by PACE. To assure comparability in billed charges over time, all charges were deflated to real terms using the CPI monthly price index for prescription drugs (base month = July 1984) *before* aggregating to the exposure period.<sup>12</sup>

---

<sup>10</sup>The reason for the uncertainty is that PACE rules require beneficiaries to re-apply for coverage every year. Some PACE beneficiaries move out of state prior to the official end of their eligibility period. For these individuals, PACE eligibility effectively ends when they move, but few if any notify PACE of their actions.

<sup>11</sup>The bias here is minor.

<sup>12</sup>"Real" prescription expense values were created by multiplying the nominal monthly billed charges incurred by each beneficiary by an appropriate deflator prior to aggregating the results to exposure period. Month-specific deflators were created using the monthly CPI for prescription drugs published by the US Bureau of Labor Statistics. July 1984 is the reference or base month, and the deflator for that month is set equal to one.



## MEAN PACE UTILIZATION AND EXPENSE RATES

Table 2 shows the annual utilization results. The following observations can be validated from the table:

- a. The demographic characteristics of the population exert a strong influence on prescription drug utilization;
- b. Males use fewer drugs than do females in every cohort and every exposure-year;
- c. Nursing home residents are consistently higher users than are the noninstitutionalized elderly;
- d. For most cohorts/exposure years, drug use rises with age up to age 84, then drops off; and
- e. Age appears to be weakly associated with utilization rate.

All of these patterns of drug use by the elderly, including the nonmonotonic age pattern, also have been observed by Gindstaff et. al. (1981), LaVange and Silverman (1987), and Moeller and Mathiowetz (1989).

As indicated, the utilization rates for the decedents should be regarded as censored variables. This is because they are not annualized. Had the rates been calculated on a per-day-of-coverage basis, the table would have shown that decedents use *more* prescription medicine during the period of exposure prior to death than do survivors over a comparable period.

**TABLE 2**  
**AVERAGE NUMBER OF PRESCRIPTION DRUG CLAIMS**  
**PER PACE BENEFICIARY PER ANNUM**

Cohort	1984				1985			1986		1987
Exposure Year	1	2	3	4	1	2	3	1	2	1
<b>Category</b>										
Total	21	24	26	27	22	24	25	20	22	21
<b>Gender</b>										
Male	19	22	23	24	20	23	24	20	21	19
Female	21	25	27	26	22	25	26	21	23	21
<b>Age</b>										
65-69	19	23	25	26	21	24	25	21	23	20
70-74	20	24	26	27	21	24	25	20	22	20
75-79	21	25	27	28	22	25	26	21	22	21
80-84	21	26	28	28	23	26	27	22	24	22
85+	21	24	25	25	23	25	25	22	22	22
<b>Residence</b>										
Noninstitutional	20	24	26	29	21	24	25	20	22	20
Nursing Home	26	28	33	33	30	32	32	30	29	29
<b>Mortality Status</b>										
Survivor	21	25	27	27	22	25	26	21	23	21
Decedent (censor)	14	17	18	19	16	17	18	16	16	15

Perhaps the most striking finding in Table 2 is the marked increase in utilization rates associated with program exposure. Drug use rose for every group of PACE beneficiaries from the first to second exposure year. The average increase was between 10 and 20 percent. The highest growth rates were for members of the 1984 cohort; the lowest for the 1986 cohort. Although there are few observation points for longer exposure periods, it would appear that the rate of utilization growth declines with exposure.

The third feature worth noting is the relative constancy of use across the cohorts when measured within a given exposure-year. For example, the average number of prescriptions filled by all beneficiaries in their first exposure-year was 20.5 (1984 cohort), 21.5 (1985 cohort), 20.8 (1986 cohort), and 20.6 (1987 cohort), respectively. After a small jump in utilization rates (less than five percent) from the 1984 to 1985 cohort, drug use in the first year of exposure for subsequent cohorts was nearly identical to the 1984 rates. With few exceptions, the same level of across-cohort stability can be seen in the utilization rates for beneficiaries within the second and third exposure years, as well as in the more detailed demographic breakdowns. Viewed from another perspective, these data provide little evidence of a general rise in drug utilization by beneficiaries over the four-and-a-half years of the study **independent** of their exposure to PACE.

Table 3 presents data on average annual prescription expenses incurred by PACE beneficiaries expressed in real (July 1984) prescription dollar values. All of the distinctive patterns associated with prescription drug utilization rates noted above are evident in these tabulations: (1) annual expense varies with demographic characteristics, (2) expense is positively associated with program exposure, and (3) beneficiaries who join PACE at different points in time exhibit similar (real) expense levels when compared according to exposure-year.

**TABLE 3**  
**AVERAGE ANNUAL REAL PRESCRIPTION DRUG EXPENSE**  
**PER PACE BENEFICIARY**

Cohort	1984				1985			1986		1987
	1	2	3	4	1	2	3	1	2	1
<b>Category</b>										
Total	295	357	390	408	319	367	389	312	344	313
<b>Gender</b>										
Male	275	329	358	373	308	354	374	303	334	297
Female	302	366	400	418	325	373	396	316	348	319
<b>Age</b>										
65-69	285	348	385	408	316	366	391	315	353	314
70-74	293	357	392	412	315	363	389	304	338	300
75-79	305	370	400	417	328	376	395	313	338	322
80-84	309	371	402	411	329	373	391	325	349	324
85+	280	329	352	357	311	347	358	297	311	302
<b>Residence</b>										
Noninstitutional	294	357	390	407	317	366	389	307	342	308
Nursing Home	332	363	426	543	394	418	420	404	393	397
<b>Mortality Status</b>										
Survivor	301	365	399	416	325	374	396	317	351	319
Decedent (censor)	211	256	277	286	238	262	280	243	246	235

**Changes in the Annual Prescription Drug Expense**

The changes in the annual prescription drug expense for PACE beneficiaries has the following components:

- $r_N$  = The nominal changes in the annual expense level;
- $r_R$  = The real changes in the annual expense level;
- $r_I$  = The inflation rate, which is the difference between the nominal and

- $r_I$  = The inflation rate, which is the difference between the nominal and real changes in annual expense levels;
- $r_U$  = The user rate, which is the increase in the percentage of beneficiaries who fill at least one prescription in a year;
- $r_n$  = The utilization rate, which is the increase in number of prescriptions filled per user; and
- $r_{PI}$  = The prescription intensity, which is the real charge per prescription filled.<sup>13</sup>

Since the inflation rate is the difference between the nominal and real changes in the annual expense levels, the relationship between these components is given by:

$$r_I = r_N - r_R,$$

where the real change in the expense level is given by:

$$r_R = (1+r_U)(1+r_n)(1+r_{PI}) - 1$$

Table 4 depicts these relationships for the PACE beneficiaries in the study sample.

---

<sup>13</sup>This factor captures the net economic impact of any shift in therapeutic regimen over and above the change in number of prescriptions filled.

TABLE 4

COMPONENTS OF CHANGE IN ANNUAL PRESCRIPTION DRUG  
EXPENSE PER PACE BENEFICIARY

Cohort & Expense Year	% Change In				
	Rx Expense per Beneficiary per Year		# Who are Users	Rx per User	Real Change Per Rx
	Nominal	Real			
$r_N$	$r_R$	$r_U$	$r_A$	$r_{PI}$	
1984					
1-2	31.4	21.1	2.0	15.3	3.0
2-3	18.1	9.3	0.0	7.7	1.3
3-4	12.7	4.5	0.0	3.4	1.3
1985					
1-2	24.1	14.9	1.2	11.6	1.6
2-3	14.4	6.1	0.0	4.1	1.9
1986					
1-2	18.9	10.3	1.5	6.8	1.9

The two most important factors explaining exposure-related growth in annual drug expense levels are inflation in prescription drug process and a rising utilization rate. Surprisingly little growth can be attributed either to higher user rates or to increased "intensity" of drugs prescribed.

One shortcoming in analyzing drug use and expense profiles by exposure-year is the length of the time-series needed to discern whether observed patterns replicate or not. Given a 54 month panel of PACE claims data, profiling experience by exposure-quarter more than quadruples the number of observations for each cohort and permits adding a fifth

cohort to the sample (persons enrolling in 1988).

## **NONPARAMETRIC ESTIMATION OF THE DISTRIBUTIONS**

Numeric frequency distributions contain more information than can be easily assimilated through visual observation. This problem can be resolved through either parametric or nonparametric techniques, or some combination of the two.

In parametric estimation a particular class of densities is chosen (e.g. normal, gamma) so that the entire distribution can be described with a few parameters. The values of the parameters are chosen so as to make the fit of the data to the estimated density as strong as possible. The difficulty is that if the wrong density class is chosen the fit will be poor regardless of the selected parameters, and extrapolations drawn from this fit may be misleading.

With nonparametric estimation no prior density or functional form is specified or imposed on the data. The best example of nonparametric estimation is the ordinary histogram. The difficulty with histograms is that when sample data are grouped into a small number of cells there is a resulting loss of sample information due to this grouping. Of course, grouping need not take place; one could plot a histogram at each integer claim level.

This section uses nonparametric techniques to produce "smoothed" versions of the annual frequency distributions for drug use and expense for each PACE cohort.

### **Empirical Limitations on the Model**

There are two important empirical limitations on the model. The first limitation is

a consequence of the fact that there are considerable observations with zero claims. As a result, it is appropriate to consider a mixed distribution with a positive probability mass at zero and a probability or density function for values greater than zero. In this instance, a mixed distribution will be used, of the form

$$p(0|z_{ij}) \delta_t + [1-p(0|z_{ij})] f_x(t|z_{ij}),$$

where  $p(0|z_{ij})$  is a positive mixing probability and  $\delta_t = 1$  if  $t=0$  and  $\delta_t = 0$  otherwise.<sup>14</sup>

The second limitation is a consequence of censoring. Because of exits from the population owing to death, lapses and late enrollments, the actual number and cost of claims is understated. The typical solution when censored data is involved is to use an iterative procedure to derive estimates of the regression parameters based on the conditional expectations of the censored values.<sup>15</sup>

### **The Raw Data**

The general nature of the raw data of the PACE study can be represented by the jagged line in Figure 1, which shows the distribution of the 1985 drug utilization rates for the members of the 1984 cohort represented in a random subsample of 12,000 beneficiaries.<sup>16</sup> The figure shows only the experience of prescription drug users, that is, the portion of the mixed distribution associated with nonzero values. This particular utilization histogram is actually one of the more regular; some other cohort/year samples

---

<sup>14</sup>See Hogg and Klugman (1984), p. 50, for a discussion of mixed distributions.

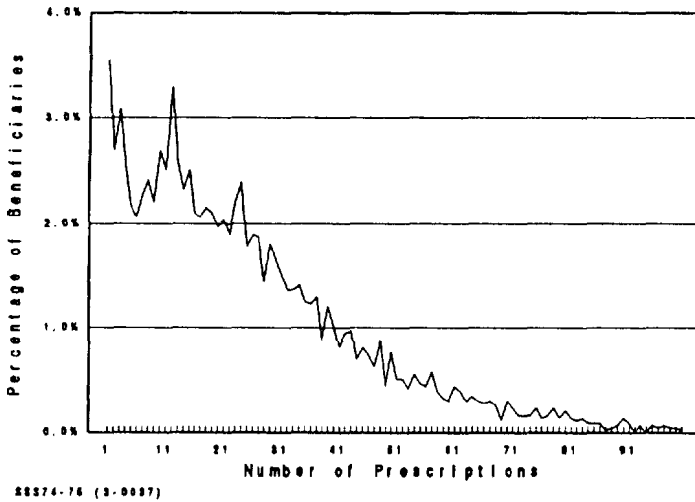
<sup>15</sup>See Kalbfleish and Prentice (1984) and Lawless (1982) for a discussion of censored regression.

<sup>16</sup>The data set for this analysis is a random subsample of 12,000 drug users selected from the 513,689 PACE beneficiaries included in the study sample. Approximately nine percent of the members in this cohort/year had no prescriptions filled through PACE.



are much more irregular than this. The point is that detailed histograms can be relatively uninformative. What is needed is some way of graduating the data without making heroic assumptions on the parametric class or information-concealing grouping procedures.

FIGURE 1  
FREQUENCY DISTRIBUTION  
1984 COHORT - 1985 PRESCRIPTIONS  
(SS87475A 3-0027)



### Graduating the Distributions

The standard Whittaker-Henderson approach to graduation,<sup>17</sup> as modified by Engle et. al. (1986), was chosen for graduating the data. The basic problem is to fit the function

---

<sup>17</sup>See London(1986), Chap. 4.

$$u_{x_n} = f_{x_n} + \epsilon_n$$

where  $x_n$  is the  $n$ -th category,  $u_{x_n}$  is the observed number of claims in that claim category,  $f_{x_n}$  is the value to be estimated, and  $\epsilon_n$  is the random error. Assuming that  $E(\epsilon_n) = 0$ ,  $\text{var}(\epsilon_n) = \sigma^2$ , and  $E(\epsilon_n, \epsilon_m) = 0, \forall n, n \neq m$ , leads to a smoothing spline approximation,  $v_{x_n}$ , which is approximately equal to  $f_{x_n}$ .

This interpolation technique imposes no assumption on the density other than the natural one that it is smooth. Smoothness is invoked through the penalty function

$$S = \sum (\Delta^2 v_{x_n})^2$$

which rewards second derivatives that are close to zero--that is, functions which are close to linear. By this definition alone, the best possible function would be a straight line. Examining the actual curve in Figure 1, it is obvious that a straight line would produce a poor fit to the raw data. Therefore, the term

$$F = \frac{1}{N} \sum (u_{x_n} - v_{x_n})^2$$

is added to the penalty function to reward good fit. Here, fit is defined as the difference between the actual and estimated frequency.

The next step is to balance the competing aims of smoothness and goodness of fit by choosing an appropriate weight for each of the two penalty function components. This is accomplished by minimizing

$$F + \lambda S, \lambda \geq 0.$$

The weight for the fit component is normalized to one, and the smoothness component weight is notated as  $\lambda$ . As  $\lambda$  gets larger, smoothness becomes more important in curve selection. When  $\lambda$  is equal to zero, the curve selected is the very unsmooth histogram shown above. As  $\lambda$  goes to infinity, the curve converges to a straight line (which correspondingly has a poor fit).

For the purpose of this analysis, the value of  $\lambda$  is determined by using the Schwarz information criterion [Schwarz (1978)]. Thus, the smoothing parameter is the one which minimizes

$$\ln(\text{RSS}) + M \ln(n),$$

where RSS is residual sum of squares, M is the number of parameters in the model, and n is the effective number of observations that is equivalent to the number of residuals that can be calculated from the series.<sup>18</sup>

Information criteria are typically used in econometric models to choose amongst models which have different numbers of parameters, so that a tradeoff between fit and low parameterization can be attained. The idea in nonparametric estimation is the same if one thinks of a smoother function (i.e. larger  $\lambda$ ) as one which implicitly has fewer parameters, but worse fit. Consider the solid curve in Figure 2 which shows the estimated frequency distribution that optimizes the Schwarz criterion at a  $\lambda$  value of 8,603. As can be seen, it

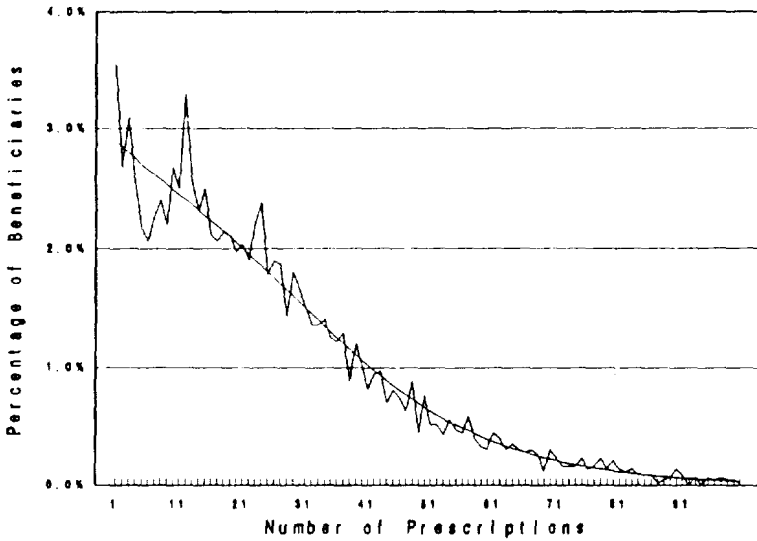
---

<sup>18</sup>Using vector notation, the logic can be summarized as follows. Assuming  $Y = Xa + e$ , the problem is to find the vector "a" that will minimize  $(1/N) \|Y - Xa\|^2 + \lambda \|Ua\|^2$ , where U is the 2nd differencing operator. The solution is  $\hat{a} = (X'X + \lambda U'U)^{-1} X'Y$ . If  $A(\lambda) = X(X'X + \lambda U'U)^{-1} X'$ , then  $\hat{y} = A(\lambda)y$  and  $e = (I - A(\lambda))y$ . The Schwarz solution is to choose the smoothing parameter " $\lambda$ " by minimizing  $\ln(e'e) + [\ln(N)/N] \ln A(\lambda)$ .

gives a much clearer picture of the skewness of the distribution, without any significant loss of sample information.

FIGURE 2  
GRADUATED FREQUENCY DISTRIBUTION  
1984 COHORT - 1985 PRESCRIPTIONS

(I-PIC 21 01B 3-0037)



### The Distribution of Number of Prescriptions

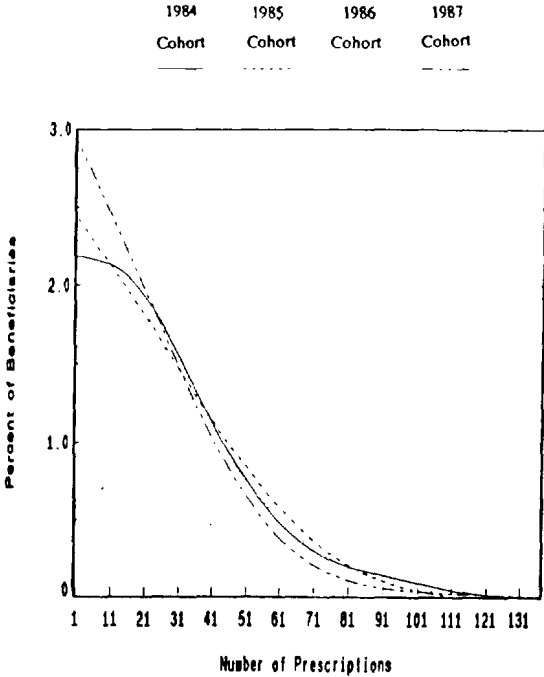
This smoothing procedure was carried out for frequency distributions of the annual number of prescriptions for users in each cohort/year combination in the dataset.<sup>19</sup> Figure

---

<sup>19</sup>For this test, "year" refers to calendar time rather than exposure period. However, there is no reason to believe that the shape of the exposure-year distributions should be any different from those calculated here.

3 shows the estimated frequency distributions associated with the 1984 PACE cohorts.<sup>20</sup> This is the most interesting cohort, since it involves four annual frequency distributions and shows the greatest amount of information. As can be seen, the frequency in annual number of prescription drugs filled by users declines uniformly through the entire range in all four years.

FIGURE 3  
 Frequency Distributions for Annual Drug Use  
 by Members of the 1984 Cohort



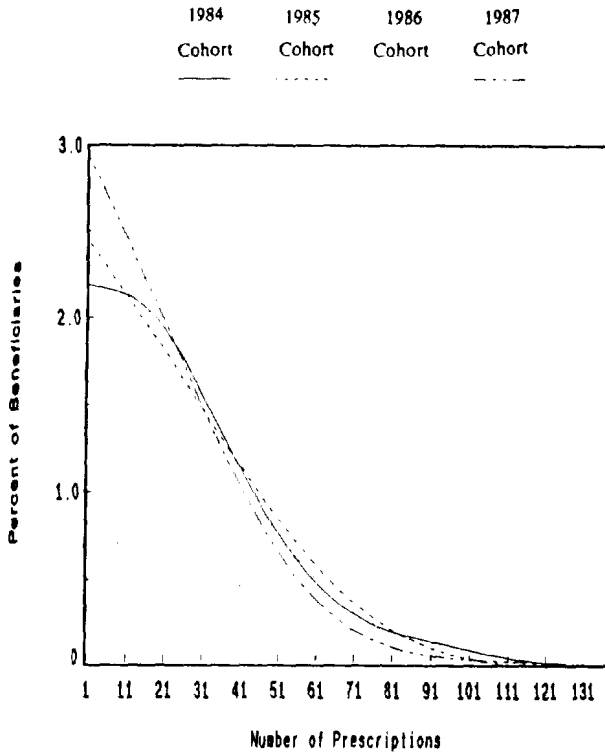
<sup>20</sup>An analysis was also done for the 1985, 1986 and 1987 cohorts. The  $\lambda$ s estimated for the 1986 and 1987 cohorts were much higher than the 1984 and 1985 cohorts. The latter were in the neighborhood of 8,000 to 9,000. The former groups had  $\lambda$ s in the 80,000 range. This indicates that the samples for these latter cohorts were much more variable (i.e. the raw histograms were more erratic) than for the earlier PACE cohorts.

Another noteworthy feature of the 1984 cohort utilization patterns is the steady and large year-to-year declines in the frequency of low-level use of the program with equivalent increases in the frequency of higher-level use. There are two possible explanations for this trend. One is that those who remain PACE enrolled through the entire four years have higher use rates than do those who subsequently die or drop out. This possibility has already been rejected. The second alternative is that the trend reflects some dynamic pattern in drug use behavior leading those with relatively low utilization rates to exhibit the most rapid increase in use over time.

The utilization experience of the 1985, 1986 and 1987 cohorts show similar patterns.

The frequency distributions of different cohorts over the same interval of time are compared in Figure 4, which shows the utilization patterns for each of the four cohorts during 1988. The only consistent ordinal pattern evident among these distributions is that the percentage of low-end users (those filling between 1 and about 15 prescriptions per year) is progressively lower among the more experienced PACE cohorts. There is no corresponding inverse relationship at the top end of the scale (although the 1984 cohort had the highest percentage of beneficiaries using over 100 prescriptions per year, the 1986 cohort placed second), nor is there any consistent relationship between frequency and PACE experience in the middle ranges. While difference in the demographic makeup of the four cohorts must be taken into account here, this picture is consistent with the view that the rise in drug utilization rates among PACE beneficiaries over time is being fueled mainly by changes in the behavior of low-end users.

**FIGURE 4**  
**Frequency Distributions of 1988 Drug Use**  
**for Four Cohorts of PACE Beneficiaries**



**The Distribution of Annual Real Expenses**

Figures 5 and 6 present smoothed distributions for annual real PACE expense following the same formats as above. The shape of these curves is virtually identical to the corresponding utilization distributions.<sup>21</sup> The one difference worth noting is in Figure 6,

---

<sup>21</sup>This result was expected because there is very little variance in the distribution of average billed charges per claim when calculated on an annual per-beneficiary basis. See Table 23 in Stuart, B., and Ahern, F., "Drug Utilization and Expenditures of Elderly Pennsylvanian PACE Program Beneficiaries: Longitudinal Cohort Analyses," Final Report under HCFA Contract ORD-88-33-008, March 1989.

which shows 1988 annual expense distributions for all four cohorts. Here it can be clearly seen that members of the 1987 cohort have the highest frequency of low-end expense and the lowest frequency of high-end expense. The reverse is true for members of the 1984 cohort. The regularity of this pattern strengthens the prior conclusion. Thus, the speculations regarding the underlying dynamics of drug spending are the same as for drug use.

Figure 5  
Frequency Distributions of Annual Real Prescription  
Expense by Members of the 1984 Cohort

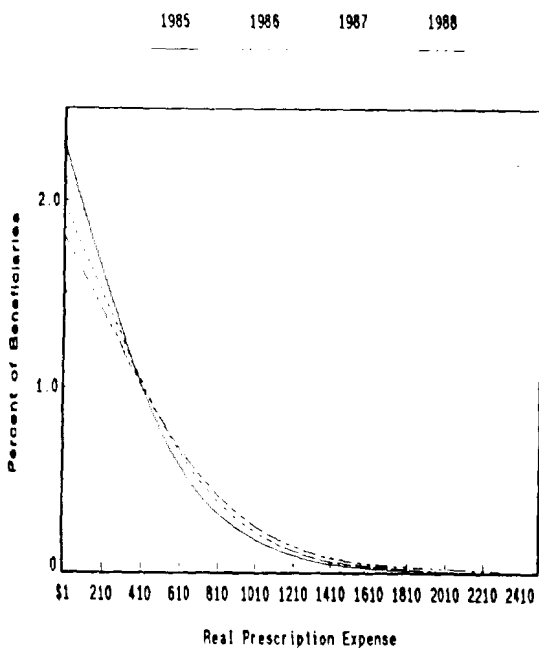
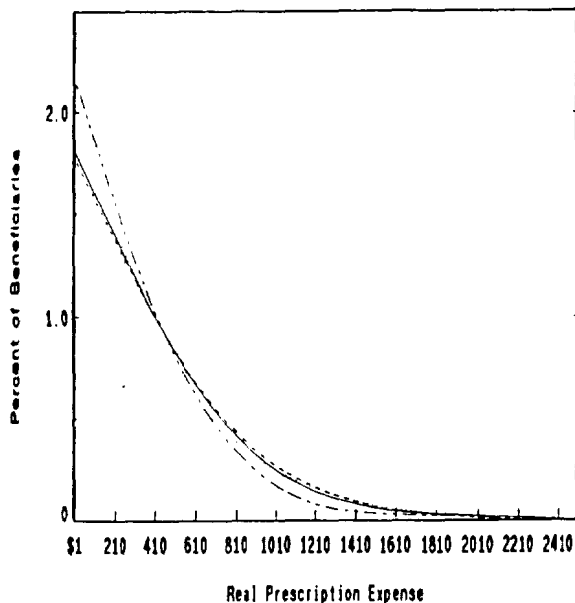




Figure 6  
 Frequency of Distributions of 1988 Real Drug  
 Expense for Four PACE Cohorts

1984 Cohort	1985 Cohort	1986 Cohort	1987 Cohort
-----	-----	-----	-----



### CONCLUSIONS AND AREAS FOR FURTHER STUDY

Four principal conclusions can be drawn from this study:

1. The utilization of outpatient prescription drugs rises with exposure to PACE coverage for all categories of PACE beneficiaries;
2. The increases in drug use appears to be fueled primarily by changes in behavior of beneficiaries at the low end of the utilization scale;
3. The temporal patterns of drug use among high users are stable and persistent; and

4. There is no evidence of any secular trend in drug use among program beneficiaries over the four-and-a-half years of the study independent of their exposure to PACE.

The remainder of this section discusses the limitations of these findings and areas for further research.

The most obvious limitation of the study is that The PACE population is not representative of the elderly at large due to program location and financial restrictions on eligibility. As a consequence, it is difficult to generalize findings beyond the sample frame.

A second potential threat to generalizability is a consequence of the adverse selection potential, since participants who enrol and continue in PACE are more likely to need prescription medicine than those who do not enroll. More analysis is necessary to determine both the magnitude of the selection effect at the point of enrollment and its persistence over time.

Insofar as other area for further research, two clear areas for further analysis are the development of parametric estimations of the distributions and the formulation of a suitable regression model. As regards the distributions, since the frequency and severity distributions are highly skewed, the Gamma or Weibull distributions may be suitable choices. As to a regression model, given the censored data, a multiplicative regression model may be appropriate.

## BIBLIOGRAPHY

- Ahern, F. M., Smyer, M. A., Lago, D., Miller, S. H., and Associates. (1988) **Medicine, Health and Aging: Enrollment in Pennsylvania's Pharmaceutical Assistance Contract for the Elderly (PACE) program.** (Report 2). University Park, PA: The Pennsylvania State University Gerontology Center and the Pennsylvania Department of Aging.
- Anderson, G. and Knickman, J. (1984) "Patterns of Expenditures Among High Utilizers of Medical Care Services," **Medical Care**, 22:2 (February), pp. 143-149.
- Baum, C., Kennedy, D., Knoop, D., and Faith, G. (1985) **Prescription use in 1984.** Paper presented at the annual meetings of the American Public Health Association, Washington, D.C.
- Beebe, J. (1988) "Medicare Reimbursement and Regression to the Mean," **Health Care Financing Review**. 9:3 (Spring), pp. 9-22.
- Beers, M., et al. (1988) Psychoactive Medication use in Intermediate-care Facility Residents. **JAMA**, 260, (20), pp. 3016-3024.
- Berry, G., Smyer, M., and Lago, D. (1988) State Level Pharmaceutical Assistance Programs for the Elderly: A National Survey. **American Journal of Public Health**, 72, (2), pp. 157-161.
- Blue, D. (1988) **Medicare Outpatient Drug Program: Preparing for the New Era.** Chevy Chase, MD, F-D-C Reports, Inc., September.
- Brown, J. (1987) Prescription Drug Cost for Older Americans. **AARP Issue Brief**, Washington, AARP Public Policy Institute.
- Crowley, John and Johnson, Richard A. (1982) "Survival Analysis," Institute of Mathematical Statistics, Lecture Notes, Vol. 2, Hayward, California, October 26-28.
- Engle, R. F., C. W. J. Granger, J. Rice, and A. Weiss. (1986) "Semi-Parametric Estimates of the Relation Between Weather and Electricity Sales," **Journal of the American Statistical Association**, 81, pp. 310-320.

- Grindstaff, G., Hirsch, B., and Silverman, H. (1981) **Medicare: Use of Prescription Drugs by Aged Persons Enrolled for Supplementary Medical Insurance, 1967-1977**. Health Care Financing Program Statistics. Office of Research, Demonstrations, and Statistics, Health Care Financing Administration. Washington, U.S. Government Printing Office.
- Hogg, Robert V. and Klugman, Stuart A. (1984) **Loss Distributions**. John Wiley and Sons.
- Kalbfleish, John D. and Prentice, Ross L. (1980) **The Statistical Analysis of Failure Time Data**, John Wiley and Sons.
- LaVange, L., and Silverman, H. (1987) Outpatient Prescription Utilization and Expenditure Patterns of Noninstitutionalized aged Medicare Beneficiaries. **National Medical Care Utilization and Expenditure Survey**. Series B, Descriptive Report No. 12. DHHS Publication No. 86-20212. Office of Research and Demonstrations, Health Care Financing Administration. Washington, U.S. Government Printing Office.
- Lawless, Jerald F. (1982) **Statistical Models and Methods for Lifetime Data**, John Wiley and Sons.
- London, D. (1986) **Survival Models and Their Estimations**, ACTEX Publications.
- Madow, William G. and Olkin, Ingram. (1983) **Incomplete Data in Sample Surveys**, Volume 3, Academic Press.
- Moeller, J., and Mathiowetz, N. (1989) "Prescription Medicines: A Summary of Use and Expenditures by Medicare Beneficiaries," **National Medical Expenditure Survey**, Research Findings 3. US, DHHS, National Center for Health Services Research and Health Care Technology Assessment, DHHS Publication NO (PHS), 89-3448, Washington, DC: GPO.
- Monyak, John T. (1990) "Use of the Accelerated Failure Time Model for the Determination of Insurance Cost," Master's paper in Statistics.
- Neter, John, Wasserman, William and Kutner, Michael H. (1985) **Applied Linear Statistical Models**, Richard D. Irwin Inc.
- Pennsylvania Department of Aging, Pharmaceutical Assistance Contract for the Elderly. (1988) **Quarterly Report to the Pennsylvania General Assembly, April 1 - June 30, 1987**. Harrisburg.

- Rubin, Donald B. (1987) **Multiple Imputation for Nonresponse in Surveys**. John Wiley and Sons.
- SAS Institute, Inc. (1985) **SAS User's Guide: Statistics**, version 5.
- Schneider, Helmut. (1986) **Truncated and Censored Samples from Normal Populations**, New York and Basel.
- Schwarz, G. (1978) "Estimating the Dimensions of a Model." **Annals of Statistics**, 6, pp. 461-464.
- Smyer, M., Lago, D., Ahern, F., Goodfellow, M., and Associates. (1986) **Medicine, Health, and Aging: Enrollment Pennsylvania's Pharmaceutical Assistance Contract for the Elderly (PACE) Program**. (Report 1). University Park, PA: The Pennsylvania State University Gerontology Center and the Pennsylvania Department of Aging.
- Stuart, B. and Ahern, F. (1989) **An Analysis of the Impact of Prescription Drug Coverage for Aged Medicare Beneficiaries**. Grant proposal submitted to HCFA, February 4.
- Stuart, B. and Lago, D. (1989) "Prescription Drug Coverage and Medical Indigence Among the Elderly," **Journal of Aging and Health**, 1:4 (November), pp. 691-709.
- U.S. Bureau of the Census. (1987) **Money Income of Households, Families and Persons in the United States**. Current Population Reports, Series P-60, No. 156. Washington, U.S. Government Printing Office.
- U.S. Congressional Budget Office. (1987) Cost estimates provided to the House Committee on Ways and Means, Subcommittee on Health.
- U.S. Office of Technology Assessment. (1987) **Prescription Drugs and Elderly Americans: Ambulatory use and Approaches to Coverage for Medicare**. Washington.
- U.S. Department of Commerce. (1987) **Statistical Abstract of the U.S., 1988**. Washington, U.S. Government Printing Office.
- Waldo, D.R. (1987) Outpatient Prescription Drug Spending by the Medicare Population. **Health Care Financing Review**, 9, (1), pp. 83-89.

