Actuarial Assessment of PACE Enrollment Characteristics in Developing Capitated Payments

FINAL REPORT

CMS Contract Number: 500-95-0061
Task Order No. 9
Univ. of WI Project Number: 144-JW15

Prepared by:

Center for Health Systems Research and Analysis
University of Wisconsin

Submitted to:

Fred Thomas, CMS Project Officer
7500 Security Boulevard
C3-20-07 Central Building
Baltimore, MD 21244-1850

November 26, 2003

Executive Summary

PACE sites face significant financial risks in providing a full range of Medicare and Medicaid services under a pre-determined monthly capitation payment per enrollee. Not only is the payment level of concern relative to the expected cost of meeting service demand, but the small size of these sites makes them prone to volatile swings in actual demand. This report addresses two aspects of this risk. First, we revisit the PACE adjustment factor used in determining the Medicare capitation payment rate. Second, we use historical PACE service records to build a site simulation model to help quantify the level of variation of actual service demand from expected results.

In the Medicare PACE adjustment analysis (Part I of the report), we combine DataPACE information on PACE enrollees from mid-1998 to mid-2000 with pre-enrollment fee-for-service (FFS) Medicare claim activity in order to predict post-enrollment FFS claims. We provide best estimates of the implied PACE adjustment factor, along with estimates of the prediction error standard deviations. The resulting estimates indicate that the PACE adjuster should vary by site, ranging from 240% to 335% of the AAPCC and averaging 280% in the first year following enrollment. The variation in site-specific adjustment factors diminishes in subsequent years as enrollee characteristics among survivors are predicted by the model to converge. The combined adjustment factor for all sites increases modestly in the years following enrollment as the enrollee cohort ages.

We found that no additional adjustment to predicted Medicare costs was needed to account for the higher mortality exhibited by PACE enrollees relative to FFS Medicare enrollees. The Medicare cost model in Part I simultaneously predicts the higher Medicare costs and mortality rates based upon the age, sex, health status and prior Medicare claims of PACE enrollees. The model's mortality estimates are consistent with DataPACE experience.

There are two sources of uncertainty for a PACE site associated with the Medicare capitation (whether we consider a system employing a fixed 2.39 adjustment factor or a future payment system based on additional site-specific factors):

- First, the PACE adjustment factor(s) is subject to error. That is, the adjustment factor does not correspond to the true expected cost of providing service to the site's enrollees.

  The error in the adjustment factor for a site may be due to "estimation error" in setting the numeric value of the factor or to "omission error" when key site characteristics which impact the expected cost of providing care are not reflected in the factor. These risks are similar to those associated with any capitation or prospective payment system and are not unique to the PACE payment system.

- Second, even if the PACE adjustment factor for a site correctly reflects the expected service demand of the site's enrollee characteristics, actual average results for the site may differ significantly from this expected level due to chance variation of individual results from expected values.

  The risk of actual results deviating significantly from expected results is greatest for small enrollee cohorts, where the results for a few individuals can have a large impact on the average results for the site.

The standard deviation of the implied PACE adjustment factor arising from both of these sources of uncertainty is approximately 30% for groups of 100 enrollees (for one year). For groups of 350, this value drops to about 15%. As the size of the enrollment group increases further, the standard deviation will continue to decrease, but not below than 10% (which is attributable to the adjustment factor estimation error which does not vary with the size of the enrollment group). This risk can be managed most effectively by pooling the experience of enrollees over time and across sites.

In the simulation analysis (Part II of this report), we use actual service records for past PACE enrollees as a sampling source for hypothetical new sites. DataPACE enrollment, assessment and service records are linked at the enrollee level to provide individual profiles of potential new enrollees. This assumes that the historical experience of past PACE enrollees will be reasonably representative of that of future enrollees. Implementing software allows the user to narrow the sampling range of sites, age groups, sex, and health statuses of selected enrollees to simulate new site results.

Results of the simulation analysis indicate that, while there is great variation in the use of specific services by individuals, combinations of Medicare and Medicaid services are much more stable. (See Table 11, for example.) In addition, the simulations indicate that the biggest source of uncertainty for a small site is the inherent variation in individual actual results from expected results, rather than recruiting a cohort of new enrollees with an atypical distribution of expected service use. As the site grows larger, the risk of recruiting an unusual group of new enrollees shrinks at roughly the same rate as the reduction in the risk of actual results varying significantly from expected results. So, the benefit of accurately reflecting, say, the ADL status of enrollees in a site's payment rates is most apparent when the variation in ADL profiles among sites is due to systematic differences in recruiting enrollees rather than to chance sampling variations. Careful use of the site simulator can help quantify the sources and magnitude of risk.

While the results of these analyses may highlight the significance of the financial risks faced by PACE sites, they do not necessarily imply that significant margins should be added to the corresponding FFS cost estimates to reduce the risk. The base rates to which an adjustment factor is applied already contain margins needed in the FFS system to cover startup costs and ongoing actual-versus-expected cost risk in that environment. The additional risk introduced by capitation (versus FFS) can be managed by pooling schemes, reinsurance agreements, reserving mechanisms, and sub-capitation arrangements.

Introduction

Background

The Program of All-Inclusive Care for the Elderly (PACE) began as a CMS demonstration program intending to replicate and test the On Lok Senior Health Services (San Francisco) care paradigm using adult day care centers to coordinate a comprehensive array of Medicare/Medicaid services. Health care and social services provided by a PACE site interdisciplinary teams are financed by monthly capitation payments from the Medicare and Medicaid programs.

The Balanced Budget Act of 1997 (BBA) makes PACE a permanent non-profit provider category within Medicare and state option within Medicaid. Implementing regulations were published in 1999 (Federal Register, November 24, 1999) incorporating the operating protocols employed in the demonstration phase. The Medicare, Medicaid and SCHIP Benefits Improvement and Protection Act of 2000 (BIPA) provides additional clarification of the flexibility afforded to PACE sites through waivers from program requirements. (See interim implementing regulations in the Federal Register, October 1, 2002.) BIPA also requires that demonstrations sites transition to permanent provider status by November 1, 2003.

CMS is currently exploring a for-profit version of PACE via a limited number of demonstration waivers and DHHS is considering a program to assist rural providers in establishing PACE sites.

The payment structure for PACE transfers all financial risk associated with provision of care and services to the site. That is, the site receives pre-determined monthly capitated payments from Medicare and from Medicaid to provide the full range of services outlined in the PACE regulations. No additional funding is available from Medicare/Medicaid should the actual cost of providing that care exceed these payments.

The Medicare capitation per member per month (PMPM) for non-ESRD enrollees has been set at 239% of the Medicare+Choice (M+C) payment rate for elderly individuals for the county in which the PACE site is located. The Medicare capitation PMPM for ESRD enrollees has been 146% and 136% of the statewide ESRD M+C rates for Part A and Part B, respectively. The Medicaid capitation rates are negotiated between the PACE organization and the state, subject to the requirement that the payment be no greater than the amount paid by the state outside the PACE program.

M+C payment rates have recently been modified to incorporate adjustments for an individual's prior inpatient diagnostic classification. CMS intends to augment this process by adding outpatient diagnostic classification adjustments. With these changes in the M+C payment structure, it is necessary to consider appropriate changes to the PACE adjustment factor used to define PACE Medicare payment rates. To date, PACE rates have been based on application of the 239% adjuster to the non-risk-adjusted demographic rates.

The magnitude of the 239% frailty adjuster has been the subject of much attention.

- RTI and CHSRA (1998) performed an analysis looking into the Medicare fee-for-service (FFS) costs of individuals meeting the nursing home certifiability standard for PACE eligibility. The key finding was that much variation in Medicare claim costs existed within the range of individuals satisfying the NHC eligibility requirement. A random sample of such individuals implied a PACE adjustment factor closer to 200% than to 239%. While actual PACE recruiting had produced enrolled populations more impaired than a random sample (suggesting an adjustment factor closer to 247%), it was recognized that future enrollees might not necessarily be so impaired and that the adjustment factor should vary from site to site based on the actual characteristics of the enrollees.

- Abt Associates (2000) estimated the first year FFS Medicare costs of actual PACE enrollees by inspecting the FFS Medicare claims of PACE applicants who remained in the FFS system rather than enrolling in PACE. The average FFS claim rates for this decliner comparison group were adjusted for differences in age, sex and prior year claim rates from PACE enrollees using regression techniques to infer the Medicare FFS costs of the PACE enrollees for the first year following enrollment. These imputed FFS costs were then compared to actual PACE site Medicare capitation rates. The results indicated that Medicare capitation rates were lower than the imputed FFS costs of PACE enrollees, while the Medicaid capitation rates showed the opposite result.

At a public meeting held on February 3, 2003, CMS presented plans for a new site-level frailty adjustment structure to be applied on top of the M+C risk adjusted rates for individuals. The risk+frailty payment system would be phased in starting in 2004 (10% risk+frailty and 90% current adjuster) and ending in 2008. Each PACE site's frailty adjuster would be based on the site's distribution of enrollee ADL impairment counts.

<u>Objectives</u>

The purpose of this analysis is to 1) revisit the Medicare PACE adjustment factor, expanding the Abt analysis beyond the first year following enrollment, and, 2) summarize the size risk PACE sites face due to actual service demand varying from expected levels.

In addition to these two primary objectives, we also address specific issues related to the implications of the high mortality rates exhibited by PACE enrollees and the joint capitation of both Medicare and Medicaid services.

Methodology

Part I of this report addresses the analysis performed to infer the FFS Medicare costs for the first five years following enrollment in PACE. This provides perspective on the appropriateness of the current 2.39 PACE adjustment factor across sites with varying enrollee characteristics. The approach is to use characteristics of actual PACE enrollees as inputs to a regression model fit to FFS Medicare claims linked to the 1994 National LTC Survey.

Enrollee characteristics included in the modeling exercise include age, sex, health status (functional and cognitive) and prior year claim rates. Age, sex and health status were taken from DataPACE records, while pre-enrollment FFS claims were provided by CMS. . Enrollees included those entering PACE from July of 1998 through June of 2000.

We provide not only best estimates of the implied PACE adjustment factor, but also the reliability of these estimates in the form of estimation and prediction error standard deviations.

Part II of this report describes the construction of a PACE site simulation model based upon monthly service use records available within DataPACE. The simulator is useful in quantifying the frequency of actual service demand exceeding expected levels. This could be used to study risk management options such as rate loadings, pooling/reinsurance schemes and reserve structures.

Data Sources: DataPACE

DataPACE is relied upon in both parts analyses described in this report. In Part I, the DataPACE enrollment and assessment records are used to describe the age, sex, ADL and cognitive status of new PACE enrollees. In Part II, the monthly service records, enrollment records, assessment records and inpatient stay records are all linked at the enrollee level to provide a longitudinal profile of each past enrollee's PACE experience. This collection of longitudinal profiles is sampled by the site simulation software to generate site-level service demand results for hypothetical new enrollee cohorts.

In the course of assembling and preparing the DataPACE files for use in the Part I and Part II analyses, some questions arose regarding its reliability. For example, the assessment records show significant variation in ADL scoring from site to site. While such variation may be due to differences in site source population characteristics and site recruiting techniques, it might also be indicative of site biases in coding ADL impairment levels

Similarly, a great deal of variation existed among sites' service record results. Again, while much of this may be due to actual differences among the sites in the care paradigms employed, some of the variation may be due to service coding differences among sites.

Initial ADL tabulations at enrollment showed a significant number of enrollees with no ADL impairments. For example, 803 of 4,581 newly capitated enrollees in 1998 through 2000 had no impairments on five ADLs (dressing, bathing, toileting, transferring and eating). However, the definition of ADL impairment excluded reliance on adaptive equipment, since this item was not available for all sites. (The On Lok portion of DataPACE resides in a database separate from that used for the other PACE sites and does not include information on adaptive equipment.) So, it may be that many of the 803 with no ADL impairments would have triggered an ADL impairment had the use of adaptive equipment been included in the definition. Furthermore, all but 50 of these 803 enrollees, had either IADL impairments, cognitive impairment or resided in nursing homes at the time they first became fully capitated. So, while they are not counted as having an ADL impairment, there are other conditions which explain their need for care.

Although the DataPACE information exhibited some suspicious characteristics (i.e., significant site variation in ADL scores, significant variation in enrollee service use patterns, and many enrollees with no ADL impairment), there is no clear indication that these are due to errors in the data. In fact, the site variation in ADL scores and service use may be attributable to real differences in the populations being served by different PACE sites, a primary focus of the analyses. Consequently, no attempts were made to filter or adjust the data prior to its use in the analyses.

If site biases do exist in recording ADL impairments or enrollee service use, there will be implications for both the Part I and Part II analyses. The Medicare FFS prediction model in Part I will not be affected since it is base on the NLTC Survey, not the DataPACE data. However, if the prediction model is applied to a site with biased ADL scores, the predicted Medicare costs will be correspondingly biased. The simulation model in Part II allows the user to filter or restrict the sampling of historical service records used to built hypothetical new enrollee cohorts. If a site's service records are suspect, the user elect to eliminate them from use.

Another challenging aspect of the DataPACE records were the gaps in monthly service records. This was most significant for On Lok, which changed database systems resulting in a period of several months in 1998 during which no service records were available. These gaps had no impact in the first analysis, but required some gap-filling interpolation for use in the simulation analysis.

The reader is cautioned to keep these data quality issues in mind while reviewing the results outlined in the remainder of this report.

Part I – Medicare Cost Model

Objective:

We wish to predict the monthly Medicare claims that might have been produced by PACE enrollees had they remained in the fee-for-service ("FFS") system rather than enrolling in PACE. Data available to address this question include information specific to existing PACE sites and claim experience for surveyed individuals in the FFS Medicare system.

PACE Data:

- DataPACE information regarding PACE enrollee age, sex and health status at enrollment. DataPACE is a database of PACE enrollment information, enrollee assessment records and enrollee monthly service use. For this part of the analysis, we use the enrollment and assessment data to describe the sex, age and health status of new PACE enrollees from July 1998 through June 2000.

- Pre-enrollment Medicare FFS claim records for those enrolling from July 1998 through June 2000. Claim records extend back 30 months prior to PACE enrollment.

While the individual DataPACE records and FFS claim records are not directly linkable (due to the lack of a common identification field in the two datasets), it is possible to infer the PACE site of the FFS claimants and link the information at the site level. So, we are able to profile the average age, sex, health status and prior FFS claim activity of each site over the two-year period.

Medicare FFS Claim Model Data:

- National Long-Term Care Survey (1994) interview data and linked Medicare FFS claims for 1993, 1994 and 1995. The NLTCS interview data provides age, sex and health status information as of the survey interview date in 1994. The 1993 and 1994 linked Medicare FFS claim records provide claim activity information for 18 months prior to the interview. The 1994 and 1995 linked claim records provide FFS claim activity for 12 months following the interview.

- The NLTCS data is used to regress post-interview FFS claims (per month) as a function of each individual's age, sex, health status and pre-interview claim activity. This is similar to the modeling performed in the 1998 RTI/CHSRA project using the NLTC Survey data. It is also similar in form to the regression modeling performed in the Abt analysis, although we fit the model to several thousand NLTC Survey records, while the Abt model was fit to a limited volume of PACE "decliner" Medicare claim records.

- The resulting regression model can be applied to the PACE site age, sex, health status (obtained from DataPACE) and pre-enrollment FFS claims (obtained from an extract provided by CMS) to predict hypothetical FFS claims for the year following PACE enrollment. Predicted FFS claims for subsequent years can be obtained by applying the regression model recursively (with adjustments relating to the effects of survivorship on costs), with each year's predicted FFS claims serving as the basis for predicting the next year's claims.

- The pre-enrollment Medicare FFS claim records provided by CMS did not contain an individual indentifier that could be linked to individual DataPACE records. Nevertheless, the site of enrollment could be deduced, so that pre-enrollment claims could be linked to the DataPACE records at the site level.

The Medicare FFS Claim Model

- Non-additive regression models require that the model be applied individually to each PACE enrollee to predict post-enrollment FFS claims and then summed to obtain aggregate results for a site or all sites. This approach is not possible without age, sex, and health status linked to prior FFS claim information linked at the individual enrollee level.
- An additive model form, on the other hand, can be applied first to the aggregate age/sex/health status DataPACE information and then to the aggregate pre-enrollment data, with the results summed to obtain the average predicted FFS claims for a PACE site

For example, consider the following non-additive and additive model forms.

<u>Non-Additive Model Example</u>:

In this example, the expected FFS claims for an individual is the sum of terms that depend on age, sex and health status, as well as a term related to prior claims for the individual. The coefficient on the prior claim component, however, depends on the age, sex and health status of the individual. This interactive term makes the model non-additive and requires that the prior claim information be linked at the individual level with the age/sex/status information in order to fit the model.

$$Y_j = a(age_j , sex_j) + b(status_j) + d(age_j ,sex_j ,status_j) X_j + e_j ,$$

where,

Y_j = FFS claims for individual j,

$a(age_j\ , sex_j)$ = model term which depends upon the age and sex of individual j,

$b(status_j)$ = model term which depends on the health status of individual j,

X_j = prior period FFS claims for individual j,

$d(age_j\ ,sex_j\ ,status_j)$ = a model coefficient which depends on the age, sex and health status of individual j, and,

e_j = model error term for individual j.

In this example, the model coefficient applied to prior period claims varies from individual to individual. Since we cannot link the age, sex and health status to the individual pre-enrollment claim records, we cannot properly compute the value of $d(age_j\ ,sex_j\ ,status_j)\ X_j$ individually or in aggregate.

Additive Model Example:

If the coefficient of X_j in the non-additive model example above is changed to no longer vary by age, sex and health status, i.e. $d(age_j\ ,sex_j\ ,status_j) = d$, then the model becomes additive.

$$Y_j = a(age_j\ , sex_j) + b(status_j) + d\ X_j + e_j\ .$$

Although we cannot apply the model to each individual enrollee, we can apply it in aggregate to all enrollees for a PACE site. If we sum the model across j for a given PACE site, we obtain,

$$\sum Y_j = \sum a(age_j\ , sex_j) + \sum b(status_j) + d \sum X_j + \sum e_j\ .$$

The fitted value of $\sum Y_j$ is the sum of two components,

$\sum a(age_j\ , sex_j) + \sum b(status_j)$, which can be computed from the DataPACE information alone, and,

$d \sum X_j$, which can be computed from the pre-enrollment claim information alone.

The error term, $\sum e_j$, is predicted to be zero.

Thus, the aggregate prediction for the PACE site can be derived so long as the regression model form is constrained to an additive structure. While this constraint may produce a less-than-optimal fit, the available models may nevertheless be adequate for the task at hand. (In restricting the model to an additive form, we cannot include interactive terms. That is, we cannot allow the effect of prior claims to vary by age, sex or health status.) Since the form of the available data does not allow us to fit a non-additive model form, we proceed with an additive model form and consider first the prediction of FFS Medicare claims for the year following PACE enrollment.

First Year After PACE Enrollment

The model form fit for the first year after enrollment in PACE has two components.

- The first component models monthly Medicare FFS claims per enrollee starting the year. Most enrollees will survive the year and contribute a full year of FFS claims to the monthly average. Other enrollees will die and contribute positive claims prior to death and no zero claims for the months following death.
- Since we prefer to estimate monthly claims per enrollee surviving to the start of that month, we need a second component to model the survivorship of PACE enrollees. The response variable of the second component is the fraction of enrollees surviving to the end of the first enrollment year.

Model Part 1:

$$Y_1 = a_{1,age,sex} + b_{1,status} + c_{1,13\text{-}18}\, X_{13\text{-}18} + c_{1,7\text{-}12}\, X_{7\text{-}12} + c_{1,4\text{-}6}\, X_{4\text{-}6} + c_{1,1\text{-}3}\, X_{1\text{-}3} + e_1,$$

where,

Y_1 = Medicare FFS claims per month per enrollee over the 13 calendar months starting with the interview month,

$X_{13\text{-}18}$ = average Medicare FFS claims per month in the six months ranging from 13 to 18 calendar months prior to the interview month, (similarly for $X_{7\text{-}12}$, $X_{4\text{-}6}$, and $X_{1\text{-}3}$),

$a_{1,age,sex}$ = fixed effect based upon the individual's age group (<75, 75 to 84, and 85+) and sex,

$b_{1,status}$ = fixed effect based upon the individual's health status, and,

e_1 = the model noise term.

Model Part 2:

$Y_2 = a_{2,age,sex} + b_{2,status} + c_{2,13\text{-}18} X_{13\text{-}18} + c_{2,7\text{-}12} X_{7\text{-}12} + c_{2,4\text{-}6} X_{4\text{-}6} + c_{2,1\text{-}3} X_{1\text{-}3} + e_2$,

where,

Y_2 = Fraction of enrollees surviving to the end of the first year of enrollment,

$a_{2,age,sex}$ = fixed effect based upon the individual's age group (<75, 75 to 84, and 85+) and sex,

$b_{2,status}$ = fixed effect based upon the individual's IADL/ADL status, and,

e_2 = the model noise term.

Note that Y_2 in the NLTCS data is based upon information linked to the survey response data indicating the date of death of individuals following the 1994 survey.

- Health statuses used in the model are based upon the individual's cognitive and functional impairment level and institutionalization status at enrollment. Six status categories are employed:

"Instit"	Institutionalized; while this is not a "health" status, it is a significant predictor of Medicare monthly FFS claim activity.
"4-5 ADLs"	Residing in community with four or five ADLs (among eating, dressing, bathing, toileting and transferring) requiring some level of human assistance (adaptive equipment alone is not considered an impairment)
"2-3 ADLs"	Two or three ADLs impaired
"1 ADL"	One ADL impaired
"IADL"	No ADLs impaired, but either one IADL (among meal preparation, shopping, housekeeping, heavy chores or money management) requiring assistance or evidence of cognitive impairment (two or more incorrect on SPMSQ or indication of dementia or other mental disorder)

“Well” No institutionalization and no ADL, IADL, or cognitive impairment

These definitions allow the health statuses to be determined from both the NLTCS questionnaires and the DataPACE assessment data. Adaptive equipment was not used as an ADL trigger because recent On Lok assessment data (which differs somewhat from the DataPACE information available from other sites) does not provide this information.

- Fitting the two model parts to the NLTCS data, we obtain:

Table 1: Medicare Cost Model

Model	T18 FFS Monthly Claims		Fraction Surviving First Year	
Component	Parameter	S.D.	Parameter	S.D.
Constant	411.50	31.20	91.64%	0.58%
Male	94.61	17.64	-1.95%	0.33%
Female	0.00	.	0.00%	.
<75	(108.20)	28.25	3.50%	0.52%
75-84	(40.46)	26.26	2.26%	0.49%
85+	0.00	.	0.00%	.
Well	(101.77)	33.19	5.55%	0.61%
IADL	80.33	36.64	3.27%	0.68%
1 ADL	360.27	54.22	0.87%	1.00%
2-3 ADLs	655.15	49.99	-2.99%	1.13%
4-5 ADLs	655.15	49.99	-5.11%	1.29%
Instit	0.00		0.00%	.
X_{13-18}	5.69%	0.79%	-0.00057%	0.00015%
X_{7-12}	10.00%	0.81%	-0.00046%	0.00015%
X_{4-6}	4.67%	0.61%	-0.00066%	0.00011%
X_{1-3}	12.02%	0.61%	-0.00100%	0.00011%

The estimated standard deviation of the model error terms are $988 and 18%, respectively. (The NLTCS sample size used to fit the models is 13,821.)

Note that the model constants represent institutionalized females aged 85 and older with no prior claim activity. Additive adjustments are made to these constants for males, for other age groups, for other health statuses and for prior FFS claim activity.

- Sample Calculation

Consider a 77-year-old female with 3 ADLs impaired and $200 prior monthly FFS claims over the past 18 months (for simplicity). She is expected to generate $411.50 - $40.46 + $655.15 + $1,000 (5.69% + 10.00% + 4.67% + 12.02%) = $1,350 per month in FFS claims over the next 13 calendar months according to the first part of the fitted model. The probability of surviving the year is similarly computed using the second part of the model to be 88.22%. Since deaths during the year are distrusted in a uniform fashion, the average exposure is (0.8822 +

1.0000)/2 = 0.9411 person-years. Dividing this into the estimated monthly cost per enrollee, we obtain the monthly cost per member per month (PMPM) of $1,435.

The model also provides the standard deviation of the estimation error (the difference between the estimate and the true expected value of monthly claims for this individual) relating to the $1,435 estimate, i.e. $48 in this case. The standard deviation of the prediction error (the difference between the estimate and the actual monthly claims the individual will generate) is $1,089. As expected, there is much greater uncertainty in predicting the actual claims of a single individual than in estimating the underlying expected monthly claim amount.

- Technical modeling notes:

    - ESRD claimants were removed from the NLTCS data.

    - Individuals with no FFS Medicare claims in the 18 months prior to the NLTCS interview were removed on the assumption that these individuals were enrolled in managed care programs outside of the FFS system.

    - Claim amounts, i.e. Y_1 and X values, were all inflated to 7/1/2000 using published USPCC values as the inflation index and were regionally adjusted using the 2000 rate schedule for aged Medicare+Choice enrollees.

Years Subsequent to the First Year of PACE Enrollment

To re-apply the model at the end of the first year to predict Medicare FFS claims for subsequent PACE years, we first need to predict the change in enrollee characteristics over the course of the first year. This is complicated by the need to focus on those who survive the first year, since those that survive will generally be younger, more female, healthier and will exhibit lower claim activity levels. So, for example, we cannot simply assume that the group of surviving enrollees will be one year older than the group starting the year. Older enrollees will experience greater mortality attrition, so the survivors will be less than one year older than the group starting the first year. Similarly, the male portion of the group will shrink relative to the female portion.

To predict the profile of the surviving cohort of enrollees, monthly health status transition rates were taken from the DataPACE information for all sites combined. These transition rates indicate the percentage of individuals starting a month in a given health status that migrate to each of eight possible ending statuses, i.e. “Well,” …, “4-5 ADLs,” and “Instit” plus “Dead” and “Disenrolled.” These transition rates depend upon the sex and age group of the individual. Applying these monthly transition rates repeatedly to a starting population of new PACE enrollees, we can estimate the age, sex and health status distribution of the individuals who survive the year.

We must also estimate the FFS claims leading up to the start of the second year in PACE, i.e. the amount that hypothetically (if the individuals had remained in the FFS Medicare system) would have been generated by the survivors in the 18 months prior to the end of the year. A reasonable estimate of this claim activity would seem to be available from the first year FFS claim estimate. However, the first year claim estimate includes claims from individuals who survive the year as well as for those who die during the year. Since those who die exhibit higher monthly claim rates than those who survive, the first year claim estimate (Y_1) would overstate the claim levels appropriate for survivors. Furthermore, Y_1 is the average for the first PACE year only; the model requires average claim levels for the prior 18 months. To overcome these problems, we make two adjustments to the first year model before applying it to the estimated surviving population.

- First, we refit the first year claim amount model and the survival model to the NLTCS data using only claims from the 12 months prior to the survey interview date. We combine these prior claims into a single monthly average for the one-year period. These new model versions are applied to the cohort of surviving enrollees using the estimated age/sex/status distribution and using a prediction of FFS monthly claims over the first year following enrollment for survivors (obtained in the next step).

- Next, we modify the response variable of the regression model. Rather than using Y_1, we use $Y_3 = Y_1 \times Y_2$, which is zero if the individual dies during the year and is Y_1 for those who survive. Dividing the estimate from this model by the estimate of Y_2, we obtain a reasonable estimate of the average monthly claim rate for those who survive the year.

- With these adjustments, we have six regression models:

  First Year after Enrollment

  FFS claims per month per enrollee starting the year:

  $$Y_1 = a_{1,age,sex} + b_{1,status} + c_{1,13\text{-}18}\, X_{13\text{-}18} + c_{1,7\text{-}12}\, X_{7\text{-}12} + c_{1,4\text{-}6}\, X_{4\text{-}6} + c_{1,1\text{-}3}\, X_{1\text{-}3} + e_1$$

  Fraction of enrollees surviving the year:

  $$Y_2 = a_{2,age,sex} + b_{2,status} + c_{2,13\text{-}18}\, X_{13\text{-}18} + c_{2,7\text{-}12}\, X_{7\text{-}12} + c_{2,4\text{-}6}\, X_{4\text{-}6} + c_{2,1\text{-}3}\, X_{1\text{-}3} + e_2$$

  FFS survivor claims per month per enrollee starting the year:

  $$Y_3 = a_{3,age,sex} + b_{3,status} + c_{3,13\text{-}18}\, X_{13\text{-}18} + c_{3,7\text{-}12}\, X_{7\text{-}12} + c_{3,4\text{-}6}\, X_{4\text{-}6} + c_{3,1\text{-}3}\, X_{1\text{-}3} + e_3$$

  Subsequent Years

  FFS claims per month per enrollee starting the year:

  $$Y_1 = a_{4,age,sex} + b_{4,status} + c_{4,1\text{-}12}\, X_{1\text{-}12} + e_1$$

  Fraction of enrollees surviving the year:

  $$Y_2 = a_{5,age,sex} + b_{5,status} + c_{5,1\text{-}12}\, X_{1\text{-}12} + e_2$$

  FFS survivor claims per month per enrollee starting the year:

  $$Y_3 = a_{6,age,sex} + b_{6,status} + c_{6,1\text{-}12}\, X_{1\text{-}12} + e_3$$

- Fitting these modified versions of the models to the NLTCS data, we obtain the following six estimated regression models:

Medicare Claim Models for First Year

Table 2: Medicare Cost Model – First Year

Model	FFS Monthly Claims (Y_1)		Fraction Surviving Year (Y_2)		FFS Survivor Claims (Y_3)	
Component	Parameter	S.D.	Parameter	S.D.	Parameter	S.D.
Constant	411.50	31.20	91.64%	0.58%	335.70	28.23
Male	94.61	17.64	-1.95%	0.33%	52.63	15.96
Female	0.00	.	0.00%	.	0.00	.
<75	(108.20)	28.25	3.50%	0.52%	(71.86)	25.56
75-84	(40.46)	26.26	2.26%	0.49%	(21.68)	23.76
85+	0.00	.	0.00%	.	0.00	.
Well	(101.77)	33.19	5.55%	0.61%	(44.93)	30.03
IADL	80.33	36.64	3.27%	0.68%	97.83	33.15
1 ADL	360.27	54.22	0.87%	1.00%	324.89	49.06
2-3 ADLs	655.15	49.99	-2.99%	1.13%	529.46	45.24
4-5 ADLs	655.15	49.99	-5.11%	1.29%	529.46	45.24
Instit	0.00		0.00%	.	0.00	.
X_{13-18}	5.69%	0.79%	-0.00057%	0.00015%	3.95%	0.72%
X_{7-12}	10.00%	0.81%	-0.00046%	0.00015%	7.87%	0.73%
X_{4-6}	4.67%	0.61%	-0.00066%	0.00011%	2.68%	0.55%
X_{1-3}	12.02%	0.61%	-0.00100%	0.00011%	8.70%	0.55%

Medicare Claim Models for Subsequent Years

Table 3: Medicare Cost Model – Subsequent Years

Model	FFS Monthly Claims (Y_1)		Fraction Surviving Year (Y_2)		FFS Survivor Claims (Y_3)	
Component	Parameter	S.D.	Parameter	S.D.	Parameter	S.D.
Constant	442.16	31.10	91.36%	0.57%	357.46	28.09
Male	102.60	17.71	-2.03%	0.33%	58.22	16.00
Female	0.00	.	0.00%	.	0.00	.
<75	(106.62)	28.39	3.47%	0.52%	(71.09)	25.64
75-84	(36.20)	26.39	2.20%	0.49%	(18.92)	23.83
85+	0.00	.	0.00%	.	0.00	.
Well	(126.04)	33.24	5.80%	0.61%	(61.62)	30.02
IADL	65.15	36.79	3.40%	0.68%	86.75	33.23
1 ADL	365.69	54.50	0.81%	1.01%	328.64	49.22
2-3 ADLs	680.76	50.20	-3.13%	1.13%	547.58	45.34
4-5 ADLs	680.76	50.20	-5.50%	1.29%	547.58	45.34
Instit	0.00	.	0.00%	.	0.00	.
X_{1-12}	28.02%	0.99%	-0.00231%	0.00018%	20.07%	0.90%

- Sample Calculation Revisited

Returning to the example used in the first year following enrollment, we now estimate FFS claims PMPM for the second year following enrollment. Recall that we need this value to use as input to the estimation of the second year claims for those who survive the first year after enrollment. We first compute estimated monthly claims for the first year following enrollment for those who survive the year. To do so, we apply the first year version of the Y_3 model above and obtain an estimated value of $1,075. Dividing by the previously computed probability of survival, 88.22%, we obtain the average monthly cost for survivors, i.e. $1,219.

It is interesting to note that, by comparing the estimated costs for first year survivors ($1,219) to the previously estimated cost for all enrollees entering the first year ($1,435), we can determine the implied cost PMPM for those who die during the first year. In this example, the estimated cost PMPM for those who die is found to be $4,669.

Next, we apply the status transition rates to estimate the health status distribution for the individual at the end of the first year. Assuming survival, the individual will be a 78-year-old female. Starting in the "2-3 ADLs" status, we find that survivors are spread across the six health statuses as follows: 0.0% "Well', 9.1% "IADL", 13.0% "1 ADL", 49.2% "2-3 ADLs", 27.4% "4-5 ADLs", and 1.3% "Instit'. Note that we force individuals in the "Well" status to disenroll at the end of the year, so that the status is empty at the start of each renewal year.

We can now apply the subsequent-year models for Y_1 and Y_3 to the estimated values applicable at the start of the second PACE year. This produces values of $1,322 and 88.12%, respectively. As in the first year, the average exposure during the second year for those starting the second year is (0.8812 + 1.0000)/2 = 0.9406. The PMPM cost is then $1,322 / 0.9406 = $1,406.

Variance of Prediction Error

The prediction error variance for the first year arises from two sources of uncertainty, parameter estimation error and sampling error, i.e. assuming that the model error term will be zero. In the second year, we have two additional sources of uncertainty. First, we have used an estimate of $1,219 for the claims occurring in the first year. Second, we have estimated the status distribution for the start of the second year. The actual results for the first year will differ from these estimates. If we compute the prediction error standard deviation in steps, we obtain the following for this example:

- Parameter estimation error: $ 51
- Plus first year monthly claim error: $ 320
- Plus status distribution error: $ 413
- Plus second year sampling error: $ 1,246

Clearly, predictions for individuals are not very reliable. However, the level of uncertainty can be reduced by pooling the individual sampling errors across a group of enrollees. For small groups, however, the volatility will still be significant. As the size of the pooling group increases, the prediction error variance of the average will shrink in proportion to the square root of the group size. For very large groups, the prediction error standard deviation will approach the parameter estimation error standard deviation, i.e. $51 in this example. (The parameter estimation error is unaffected by the size of the enrollee group; it is determined by the size of the dataset used in fitting the regression model, i.e. the volume of data in the NLTCS.)

In the next section, we leave this hypothetical example and apply the model to new enrollee cohorts from PACE sites.

Predicted Results for PACE Enrollees

- To use the previous the models to predict Medicare costs for the first five years following enrollment, we assemble the age/sex distribution, the health status distribution and the average monthly pre-enrollment amounts by PACE site (for those individuals enrolling from July 1998 to June 2000). These values are shown in the table below.

Average Age and Sex at PACE Enrollment (7/1998 – 6/2000)

Table 4: PACE Age and Sex Distribution

Site	Count	Female	Age
Bronx, NY	230	61.7%	75.5
East Boston, MA	183	78.1%	79.8
Portland, OR	169	76.9%	77.9
Columbia, SC	168	76.8%	77.1
Milwaukee, WI	180	75.6%	77.2
Schenectady, NY	84	81.0%	77.7
El Paso, TX	180	67.8%	78.2
Denver, CO	144	68.8%	81.0
Rochester, NY	99	56.6%	78.1
Chattanooga, TN	117	76.9%	76.2
Dorchester, MA	39	76.9%	78.0
Cleveland, OH	97	85.6%	77.7
North Syracuse, NY	98	85.7%	78.9
Cincinnati, OH	97	76.3%	77.6
Detroit, MI	129	82.2%	80.2
Seattle, WA	168	71.4%	77.9
Los Angeles, CA	103	76.7%	79.7
Sacramento, CA	97	72.2%	77.8
Oakland, CA	112	56.3%	76.9
San Francisco, CA	374	68.7%	79.6
All PACE	2,870	72.6%	78.2
All FFS	n/a	60.9%	75.3

Health Status at PACE Enrollment (7/1998 – 6/2000)

Table 5: PACE Health Status Distribution

Site	Well	IADL	1 ADL	2-3 ADLs	4-5 ADLs	Instit
Bronx, NY	2.2%	30.4%	13.9%	20.0%	33.0%	0.4%
East Boston, MA	0.0%	6.6%	17.5%	48.1%	19.7%	8.2%
Portland, OR	0.0%	20.7%	22.5%	27.8%	28.4%	0.6%
Columbia, SC	0.0%	3.0%	7.7%	32.7%	56.5%	0.0%
Milwaukee, WI	0.0%	30.6%	17.2%	30.0%	22.2%	0.0%
Schenectady, NY	0.0%	9.5%	19.0%	39.3%	20.2%	11.9%
El Paso, TX	0.0%	23.3%	9.4%	27.2%	39.4%	0.6%
Denver, CO	0.0%	19.4%	16.7%	24.3%	37.5%	2.1%
Rochester, NY	0.0%	4.0%	2.0%	33.3%	55.6%	5.1%
Chattanooga, TN	0.0%	4.3%	6.0%	39.3%	49.6%	0.9%
Dorchester, MA	0.0%	15.4%	12.8%	30.8%	41.0%	0.0%
Cleveland, OH	0.0%	1.0%	8.2%	34.0%	55.7%	1.0%
North Syracuse, NY	0.0%	4.1%	6.1%	49.0%	40.8%	0.0%
Cincinnati, OH	0.0%	21.6%	9.3%	30.9%	26.8%	11.3%
Detroit, MI	0.0%	22.5%	18.6%	34.1%	21.7%	3.1%
Seattle, WA	0.0%	7.1%	13.1%	14.3%	64.3%	1.2%
Los Angeles, CA	0.0%	5.8%	5.8%	46.6%	37.9%	3.9%
Sacramento, CA	0.0%	19.6%	17.5%	30.9%	27.8%	4.1%
Oakland, CA	0.9%	27.7%	14.3%	26.8%	30.4%	0.0%
San Francisco, CA	0.0%	13.1%	15.8%	28.9%	33.2%	9.1%
All PACE	0.2%	20.7%	22.5%	27.8%	28.4%	0.6%
All FFS	74.3%	13.2%	2.8%	2.0%	1.5%	6.1%

When comparing these ADL/IADL values to other published DataPACE tabulations, we need to consider the following:

- These values are restricted to new enrollees over a two-year period, as opposed to all enrollees in the program at a given point in time.

- These ADLs considered are limited to five that match up well with those available from the NLTC survey. The grooming ADL available in DataPACE was ignored for this reason.

- Institutionalized individuals are placed in a separate status category in the table above. This complicates direct comparisons with tabulations based solely on ADL count.

- In the table above, individuals are not counted as impaired in an ADL if they only require adaptive equipment to perform the activity. (This was done to allow use of the new On Lok data, which does not include the adaptive equipment information available in regular DataPACE.) Other ADL tabulations may consider adaptive equipment a valid ADL triggering condition.

- Recall that the IADL group is composed of non-institutionalized enrollees unimpaired in any of the five ADLs, but exhibiting some IADL or cognitive impairment.

Pre-Enrollment Monthly Medicare Claims (Regionally Adjusted as of 7/1/2000)

Table 6: PACE Pre-Enrollment Medicare Claims

Site	X_{1-30}	X_{19-30}	X_{13-18}	X_{7-12}	X_{4-6}	X_{1-3}
Bronx, NY	649	360	548	975	1,251	751
East Boston, MA	1,011	817	846	1,119	1,452	1,466
Portland, OR	551	371	277	865	900	840
Columbia, SC	811	515	575	895	1,794	1,318
Milwaukee, WI	802	569	604	1,018	1,724	774
Schenectady, NY	1,137	876	776	1,371	2,198	1,372
El Paso, TX	1,062	837	810	946	2,380	1,378
Denver, CO	833	651	684	800	1,499	1,261
Rochester, NY	1,095	679	812	1,346	2,287	1,636
Chattanooga, TN	1,151	1,135	1,118	1,201	1,441	889
Dorchester, MA	1,192	1,228	1,165	1,200	1,352	928
Cleveland, OH	831	624	990	952	1,185	741
North Syracuse, NY	1,462	1,325	1,655	1,435	1,678	1,458
Cincinnati, OH	898	899	950	1,068	739	608
Detroit, MI	870	714	670	981	1,645	898
Seattle, WA	833	583	906	981	1,224	998
Los Angeles, CA	774	617	767	1,051	964	673
Sacramento, CA	913	553	933	1,178	1,552	1,144
Oakland, CA	756	595	533	772	1,544	1,022
San Francisco, CA	837	405	509	788	1,935	2,221
All PACE	891	670	747	1,011	1,550	1,158
All FFS	n/a	n/a	359	357	383	405

The table above shows the average monthly FFS Medicare claims for the 30 months prior to PACE enrollment by site and (in the last row) the corresponding values for FFS Medicare individuals based upon the 1994 NLTCS sample. (Recall that the NLTC Survey data includes linked Medicare FFS claim records for the years containing and surrounding the survey date.) The first column of values is the average over all 30 months. The remaining columns show average monthly FFS claims for various periods leading up to PACE enrollment. The values for 19 to 30 months prior to enrollment are included for information only, since the NLTCS-based regression model only uses claims in the prior 18 months.

Note that the values in the table above have been inflated to 7/1/2000 using USPCC values and have been regionally adjusted to a national basis using the 2000 Medicare+Choice regional rate schedule for elderly Medicare individuals. This is consistent with the adjustments applied to the 1994 NLTCS data used to fit the cost model.

So, the observed increases over time in monthly FFS claims are not due to inflation. In the case of the pre-enrollment PACE claims, the increases are likely due to worsening health which triggers the need for PACE services. For the FFS Medicare population (the last row of the table), the increase is likely due to a survivorship effect. The individuals generating claims in the early pre-survey period are known to survive a year. The individuals generating the later pre-survey claims are only known to survive a few months. Thus, the earlier group is more “select” in its composition. The selection effect wears off as we consider groups nearer to the NLTCS survey date.

Also note that PACE enrollees with no FFS Medicare claims in the 18 months prior to enrollment were removed prior to computing the average monthly FFS claim rates, on the assumption that they were most likely enrolled in managed care programs. While this may also remove a small number of individuals in FFS with no claims during the period, we believe the impact on the analysis is negligible. This filtering scheme is consistent with the treatment of NLTCS respondents with no linked FFS claims in the 18 months prior to the 1994 survey.

The increase in monthly FFS claims prior to PACE enrollment is consistent with the assumption that many PACE enrollments are motivated by a triggering event, i.e., a change in the individual’s health status that prompts a need for additional assistance. For many sites (and for all sites combined), the pre-enrollment claim rate peaks four to six months prior to enrollment and diminishes during the three months just prior to entry. This might be attributed to a survival effect. That is, those who experience an acute health episode (triggering event) and survive to enroll in PACE could reasonably be expected to exhibit a reduction in the acute care claim rate before entering PACE. The lag between the triggering event and PACE enrollment will determine whether the pre-enrollment claim peak occurs in the first or second quarter prior to entry.

In the Abt study, Medicare FFS claims were summarized for the 12 months prior to the PACE application home visit, which occurred throughout 1995 to 1997. The average monthly claims observed, inflated to 7/1/2000, was approximately $1,600. Using the information in the table above, with the regional adjustments removed, for the same sites studied by Abt, the comparable monthly claim rate from this analysis is approximately $1,400.

Using the age, sex, health status and pre-enrollment claim information as input to the Medicare claim model, we obtain the following estimated FFS claims PMPM.

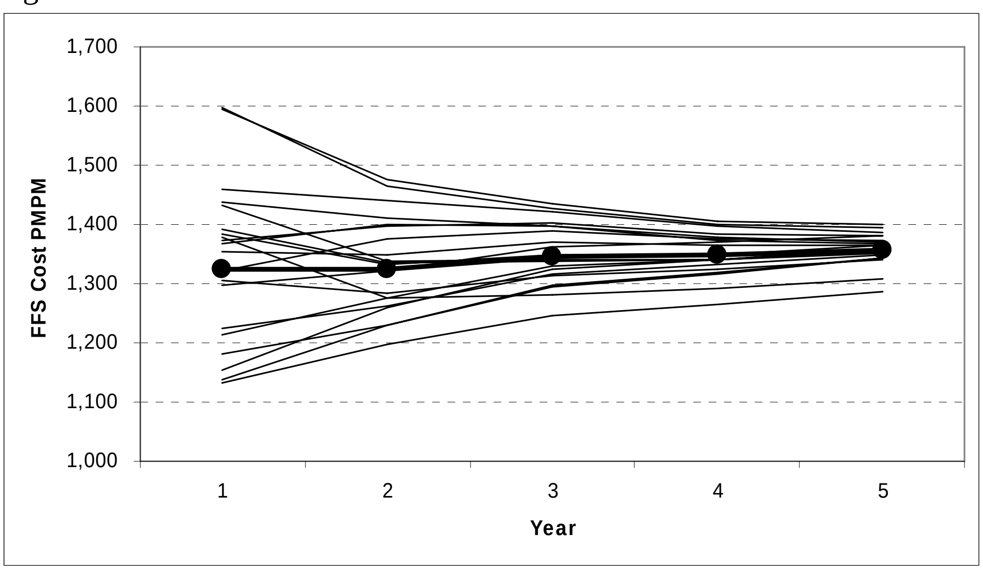
Medicare FFS Claims PMPM by Year Since Enrollment

Table 7: Predicted Medicare FFS Costs

Site	Count	Yr 1	Yr 2	Yr 3	Yr 4	Yr 5
Bronx, NY	230	1,138	1,230	1,297	1,320	1,343
East Boston, MA	183	1,392	1,334	1,339	1,340	1,352
Portland, OR	169	1,154	1,258	1,325	1,339	1,355
Columbia, SC	168	1,460	1,441	1,423	1,397	1,386
Milwaukee, WI	180	1,181	1,230	1,294	1,317	1,343
Schenectady, NY	84	1,378	1,275	1,280	1,292	1,307
El Paso, TX	180	1,383	1,332	1,348	1,350	1,365
Denver, CO	144	1,297	1,322	1,362	1,369	1,382
Rochester, NY	99	1,595	1,475	1,435	1,405	1,399
Chattanooga, TN	117	1,437	1,412	1,397	1,374	1,367
Dorchester, MA	39	1,354	1,350	1,371	1,364	1,364
Cleveland, OH	97	1,366	1,399	1,398	1,379	1,370
North Syracuse, NY	98	1,597	1,465	1,427	1,401	1,396
Cincinnati, OH	97	1,131	1,196	1,246	1,265	1,286
Detroit, MI	129	1,224	1,262	1,316	1,332	1,349
Seattle, WA	168	1,373	1,398	1,403	1,385	1,381
Los Angeles, CA	103	1,323	1,376	1,390	1,375	1,373
Sacramento, CA	97	1,306	1,283	1,312	1,324	1,341
Oakland, CA	112	1,214	1,276	1,329	1,341	1,360
San Francisco, CA	374	1,431	1,337	1,342	1,341	1,354
All PACE	2,870	1,325	1,324	1,347	1,348	1,358

These results are shown graphically in the following figure.

Figure 1: Predicted Medicare FFS Costs



The darker line with dots represents all PACE sites combined. Note that the projected costs converge as time passes. This is due to the gradual dilution of the initial variation across sites of pre-enrollment monthly claim amounts in the modeling of each successive year from enrollment. That is, the variation in X-values prior to enrollment causes the first year estimates to vary from $1,100 to

$1,600 PMPM. The prior year X-values used as input for predicting the second year costs PMPM are obtained from the first year model, which assumes zero sampling error during the first year and produces less varied monthly claim averages across sites. So, the impact of the variation in pre-enrollment claims by site dies out as the forecast is extended further into the future.

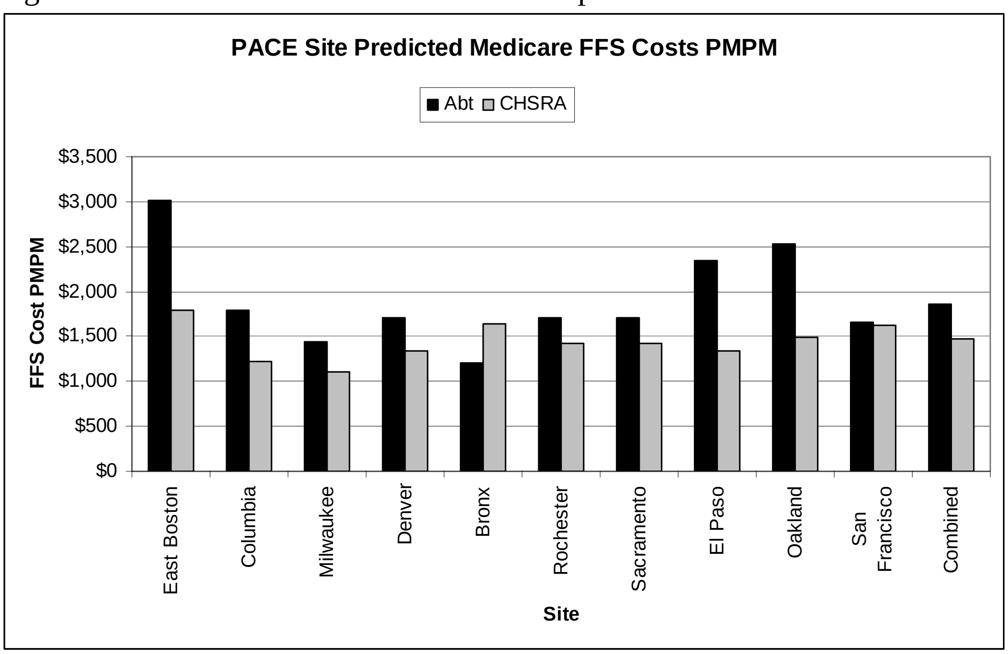
The remaining site-to-site variation is due to age/sex/health status differences across sites. Even this variation diminishes over time. The model projection uses the same monthly status transition rates for all sites (based upon historical transitions for all sites combined). Repeated application to sites with different health status distributions at enrollment results in surviving populations with converging distributions.

The combined site results increase due to a gradual aging of the surviving population.   Note that all of the claim values have been indexed to 7/1/2000 (as well as regionally adjusted to a common national basis), so that there is no inflation incorporated into the cost progression displayed.

- Comparison to Abt Study Model

Table 5.3 of the Abt study final report summarizes the basic regression model used to predict post-enrollment FFS claims. The model includes terms for sex, age, site effects and prior period claim effects. The figure below compares the predicted monthly FFS claims for the first year following enrollment derived from the Abt model and from the current model.

Figure 2: Predicted Medicare FFS Cost Comparison



Note that the Abt model predictions have been inflated to 7/1/2000 and the regional adjustments have been removed from the current model predictions.

- PACE Adjustment Factors

We define the adjustment factor as the ratio of the expected cost PMPM for PACE enrollees to the average expected cost PMPM applicable to the entire FFS Medicare population. To obtain the denominator of the adjuster, we apply the model to the characteristics of the entire FFS Medicare system (shown in the last row of the tables above). The expected average monthly claim amount (Y1) for FFS Medicare individuals is found to be $469 while the probability of surviving the year (Y_3) is computed to be 96.92%. The exposure over the year is then (0.9692 + 1.0000)/2 = 0.9846 person-years and the PMPM cost is $469 / 0.9846 = $476. This value, which has been indexed to 7/1/2000, is reasonably close to the 2000 USPCC value of $464. We do not project this beyond the first year, since we assume that those comprising Medicare FFS form a stationary population. That is, those that die during the year are replaced by new Medicare enrollees so that the characteristics of the entire population remain largely unchanged. So, the $476 cost PMPM is assumed to remain constant as a comparison base for the close cohort of PACE enrollees.

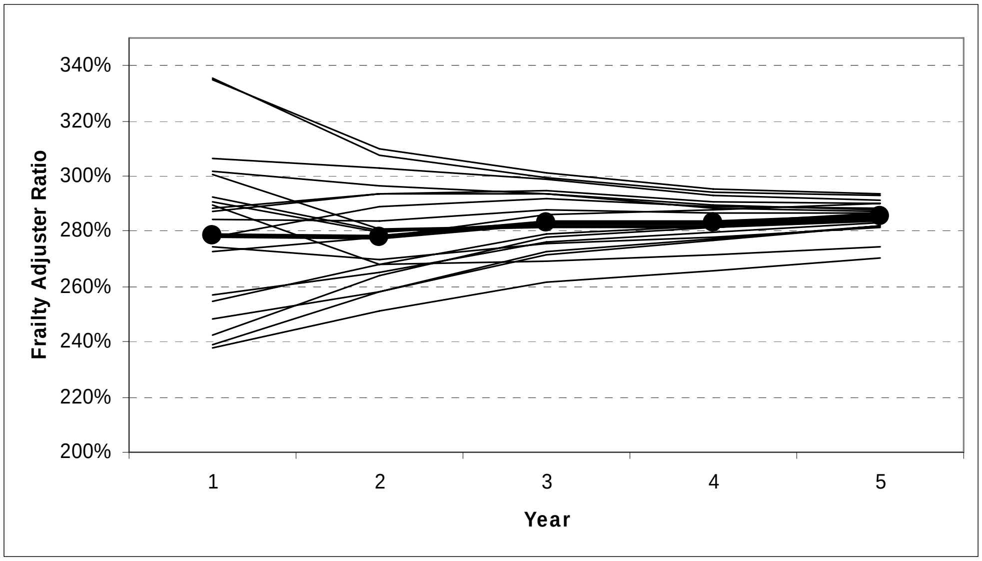
Dividing the $476 PMPM cost for all FFS Medicare individuals into the predicted PACE PMPM costs, we obtain implied adjustment factors for each site.

Implied Adjustment Factors by PACE Site and Year from Enrollment

Table 8: PACE Adjustment Factors by Site and Year

Site	Yr 1	Yr 2	Yr 3	Yr 4	Yr 5
Bronx, NY	239%	258%	272%	277%	282%
East Boston, MA	292%	280%	281%	281%	284%
Portland, OR	242%	264%	278%	281%	285%
Columbia, SC	307%	303%	299%	293%	291%
Milwaukee, WI	248%	258%	272%	277%	282%
Schenectady, NY	289%	268%	269%	271%	275%
El Paso, TX	290%	280%	283%	283%	287%
Denver, CO	272%	278%	286%	288%	290%
Rochester, NY	335%	310%	301%	295%	294%
Chattanooga, TN	302%	297%	293%	288%	287%
Dorchester, MA	284%	283%	288%	286%	287%
Cleveland, OH	287%	294%	294%	290%	288%
North Syracuse, NY	335%	308%	300%	294%	293%
Cincinnati, OH	238%	251%	262%	266%	270%
Detroit, MI	257%	265%	276%	280%	283%
Seattle, WA	288%	294%	295%	291%	290%
Los Angeles, CA	278%	289%	292%	289%	288%
Sacramento, CA	274%	270%	276%	278%	282%
Oakland, CA	255%	268%	279%	282%	286%
San Francisco, CA	301%	281%	282%	282%	284%
All PACE	278%	278%	283%	283%	285%

Figure 3: PACE Adjustment Factors by Site and Year



Of course, this graph is the same as the PMPM cost graph previously presented, except that the scale has been changed by dividing throughout by $476.

- Adjustment Factor Prediction Error

The numerator of the adjustment factor is subject to the same sources of uncertainty outlined in the first and subsequent year sample calculations for the 77-year-old female. The denominator ($476) is subject only to parameter estimation error. Using the variances and covariances of the estimated model parameters along with the variance and covariances of the model error terms, we can approximate the standard deviation of the adjustment factor prediction error for each PACE site.

Standard Deviation of Adjustment Factor Prediction Error – First and Second Year

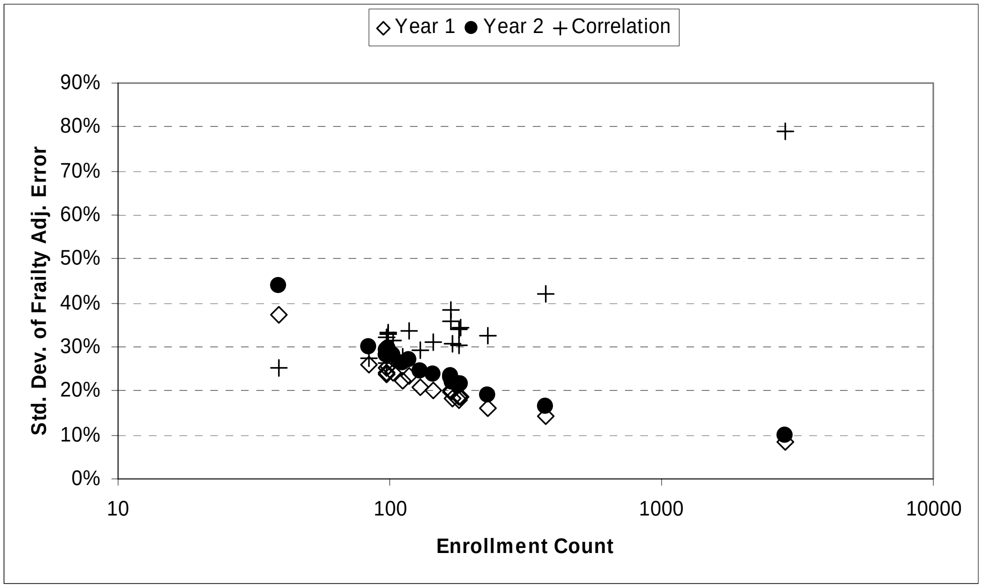
Table 9: Adjustment Factor Prediction Error Standard Deviations

		Adjustment Factors		Standard Dev. Error		
Site	Count	Yr 1	Yr 2	Yr 1	Yr 2	Corr
Bronx, NY	230	239%	258%	16%	19%	32%
East Boston, MA	183	292%	280%	19%	22%	35%
Portland, OR	169	242%	264%	18%	22%	31%
Columbia, SC	168	307%	303%	20%	23%	38%
Milwaukee, WI	180	248%	258%	18%	21%	31%
Schenectady, NY	84	289%	268%	26%	30%	27%
El Paso, TX	180	290%	280%	19%	22%	34%
Denver, CO	144	272%	278%	20%	24%	31%
Rochester, NY	99	335%	310%	25%	29%	33%
Chattanooga, TN	117	302%	297%	23%	27%	34%
Dorchester, MA	39	284%	283%	37%	44%	25%
Cleveland, OH	97	287%	294%	25%	29%	32%
North Syracuse, NY	98	335%	308%	26%	29%	33%
Cincinnati, OH	97	238%	251%	24%	28%	26%
Detroit, MI	129	257%	265%	21%	25%	29%
Seattle, WA	168	288%	294%	20%	23%	36%
Los Angeles, CA	103	278%	289%	24%	28%	31%
Sacramento, CA	97	274%	270%	24%	28%	28%
Oakland, CA	112	255%	268%	22%	26%	28%
San Francisco, CA	374	301%	281%	14%	16%	42%
All PACE	2,870	278%	278%	9%	10%	79%

The table above shows best estimates of the site-specific adjustment factors for the first and second year following PACE enrollment, standard deviations of the estimation error for each, and the correlation between the first and second year estimation error. For example, consider the Denver PACE site. Based upon the pre-enrollment FFS claim history and the sex/age and health status at enrollment of the 144 enrollees, PMPM Medicare FFS claims would have been expected to be 272% and 278% of the $476 average FFS monthly cost in year 1 and year 2, respectively. However, we know that the actual average monthly cost for this cohort will vary from the expected value. The 20% standard deviation in the first year tells us that roughly 5% of the time actual claims will produce an average monthly cost that is more than 40% (2 times the 20%) above or below the expected 272% frailty ratio. That is, we are 95% confident that the actual frailty ratio for the first year will be greater than 232% and less than 312%.

Standard Deviations of Adjustment Factor Prediction Errors for First and Second Year after PACE Enrollment versus Enrollment Count

Figure 4: Adjustment Factor Prediction Error Standard Deviations



As expected, the adjustment factor estimate becomes more reliable as the size of the PACE site increases due to the pooling of a larger number of model error terms. As the sampling error is diluted with larger cohorts, the parameter estimation error becomes the dominant source of uncertainty in the adjustment factor estimate. Since this error source is common to the first and second year estimates, the correlation between the two years becomes stronger as the sampling error fades.

As the PACE site size increases, the error variance decreases asymptotically to the level attributable to parameter estimation error, which depends upon the size of the regression model database (1994 NLTCS), not the size of the PACE site to which the model is subsequently applied. This minimum error standard deviation is approximately 7% for the first year and 9% for the second year.

- While it is important to recognize the risk level faced by small sites, it does not follow necessarily that small sites should be paid more PMPM than large sites by Medicare in order to reduce the risk they face.

  Within the average FFS cost basis there is an implicit margin to cover the economic costs of the risk of adverse deviation and startup costs. The market for FFS Medicare services requires such a margin. The implied "risk" margin is that for an average-sized FFS provider.

A PACE site developer, knowing the risk associated with sites of various sizes, can choose to manage that risk by pooling it across other PACE and non-PACE sites, by reinsurance agreements, or by a variety of sub-capitation schemes to pass the risk on to contracted providers (hospitals, nursing homes, etc.).

So, unless CMS wishes to promote and pay for "smaller-than-average" Medicare service provider configurations, there is no need to load the average FFS claim costs in setting PACE site payment rates.

Measurement of the site financial risk is needed to insure that proper steps are taken by site management to assure that adequate resources are available to cover the periodic shortfalls that will occur with greater frequency for small sites than for larger sites. Such steps might include establishing risk reserves and arranging for reinsurance.

- As expected, the estimated frailty adjuster ratios are greater than that estimated from CHSRA's 1998 analysis, which focused on PACE sites formed as random samples of Nursing Home Certifiable Medicare enrollees. Existing PACE sites have historically recruited a more frail population than the average NHC Medicare enrollee.

  A major issue is the expected profile of future PACE site populations. If similar to existing sites, continued use of the 2.39 frailty adjuster will generate capitation payments that are less than the hypothetical FFS claims that might otherwise have been generated had the individuals not enrolled in PACE. If future PACE profiles are skewed toward less impaired NHC populations, the 2.39 factor may be too great (as demonstrated by the CHSRA 1998 study).

Part II – PACE Site Service Variation

Objective:

In Part I, we concentrated on the hypothetical Medicare FFS costs that PACE enrollees might have generated had they remained in the FFS system. In Part II, we inspect the actual service utilization of PACE enrollees after entering the PACE program. Specifically, we assess the utilization risk arising from variation in monthly service demand using site simulation software.

PACE Data:

We employ DataPACE service information, i.e. 314,228 monthly records associated with 10,895 enrollees over a period ranging from before 1990 through 2000. These service records were linked to DataPACE assessment, enrollment and inpatient stay records so that we can observe changes over time in health status, as well as PACE service use. The experience is limited to capitated months for Medicare/Medicaid dual-eligible enrollees.

Enrollment Simulator:

Historical PACE site service records provide an indication of the type of variation in service demand that may be experienced by sites in the future. However, the number of site enrollment cohorts that are available for review are limited to roughly 20 sites over ten years. While this provides some indication of expected service levels, it doesn't provide much insight into the likely variation from these expected levels. To leverage the available date to the greatest extent, we use the historical service data to calibrate a simulation model of individual enrollee service monthly use. Such a model can be repeatedly run to accumulate a very large volume of simulated experience from which we can easily obtain estimates of expected service use as well as variation about these expected levels. There are (at least) two possible approaches to constructing such a simulator.

- Parametric stochastic model: With this technique, we decompose the service utilization process into component parts, estimate the means, variances and covariance associated with each part from past data, simulate future experience for each part, and assemble the final simulated service use from these part for each individual.

  For example, we might assume that monthly service use for an individual depends upon the age, sex, cognitive, functional and medical status of the individual. So, to simulate service use, we must first simulate changes in the individual's health status over time. If we define, say, ten health statuses (combinations of cognitive, functional and medical classifications), then for each sex and age group we must estimate 10 x 10 = 100 monthly transition probabilities. If we have four age groups, this requires 2 x 4 x 100 = 800 values to be estimated. For each sex, age group and health status, we must the estimate the expected monthly service use for each type of service of interest. The DataPACE monthly service records provide roughly 70 service measurements each month. Suppose we consolidate these services into half a dozen values of interest. Then we have 2 (sexes) x 4 (age groups, for example) x 10 (statuses) x 6 (services) = 480 expected values to estimate from the historical data. Estimating these 480 values along with the 800 transition probabilities is not inconceivable; there are simplifying model assumptions to greatly reduce the number of parameters needing estimation. The difficulty with this approach lies in the number of variances and covariances that must be estimated. The six monthly service values are correlated to each other and to their prior values for an individual. In addition, expected service use may also depend upon how long an individual has resided in a particular health status. It become apparent quickly that this approach to modeling requires significant data, effort and care.

Early modeling efforts for this project began as parametric models. As these simulation models were expanded, the number of structural assumptions and parameters quickly become unwieldy. Errors in either the model structure or the parameter estimates can compound to make the simulated results unreliable. We eventually decided to utilize the following non-parametric modeling approach.

- Non-parametric resampling: With this technique, we form simulated future enrollees by sampling directly from the pool of past enrollees. That is, we randomly select prior enrollees to represent future enrollees. To simulate a cohort of 20 new enrollees, for example, we pick 20 individuals (possibly from different sites and enrollment periods) and use their actual age, sex, health status and service use histories. We can repeatedly select groups of 20 enrollees (possibly re-selecting the same individual many times) and summarize the average results and the variation in average results from sample to sample.

  The disadvantage of this technique, is that it requires complete, uncensored histories. "Complete" means that there are no holes (missing variables or gaps in the availability) in the progression of monthly service records. Unfortunately, there are several situations in which a sequence of monthly service records is interrupted. (Several such gaps are due to the transition from DataPACE by On Lok to a separate database system.) To overcome this problem, we filled such gaps by repeating the last monthly service record available prior to the gap. (We also incremented the person's age month by month.) While it is somewhat arbitrary, the gaps are typically short and this fix eliminated to need to discard a sizeable block of On Lok experience.

  "Uncensored" means that the available sequence of records cannot be terminated by the end of the study period (12/31/2000 in this case). If we wish to simulate three years of experience following enrollment, we are limited to individuals who enrolled prior to 1998. The longer the desired period of observation, the smaller and older will be the useable data. (Note that we cannot include individuals who enroll in or after 1998 and die prior to the end of 2000. Such individuals are a biased sample of experience from that period.)

A final, more subtle, problem with this re-sampling scheme is that it assumes that the experience of each individual is independent of that of every other individual. While this may not seem to be a contentious assumption, consider the following possibility. Suppose that a PACE site rations the services it provides each month due to a shortage of staff or other resources. The experience taken from such sites and time periods will not accurately reflect service demand, only service provided. The experience of individuals in this setting may be positively or negatively correlated, rather than independent. If all enrollees receive less than expected service levels, their experience is positively correlated. If provision of services to one individual implies that another will receive less than expected, the experience is negatively correlated. For our purpose, we do not believe that this is significant enough to invalidate the results. Nevertheless, the reader should be aware or the underlying independence assumption.

- There is significant variation in monthly service patterns from site to site. While this may be an indication that some sites are more lax than others in recording certain services, it may also be due to differing care paradigms from site to site. The site simulator allows the user to restrict individuals case histories to a those from a specific site or group of sites. So, if there is no confidence in the records of Site A or it is believed that the future site will employ a recipe for care similar to that of Site B, the user can exclude the questionable Site A histories and/or limit the sampling to records from Site B.

  Drawing individual case histories from a pool which includes several sites, may dilute any data validity risk, it will not eliminate the problem if it exists. If we take the variation in site service patterns as an indication of a data validity issue, then sampling individual records from all sites will over-estimate risk associated with variation in actual service demand from expected levels.

- Simulator software: The simulator is implemented by Visual Basic code attached to an Excel spreadsheet. The user specifies the characteristics of the simulation source records, such as the maximum enrollment year, the health status at enrollment (e.g. “1 ADL”, “2-3 ADLs”, or some mixture), the age group and sex. The simulator then forms 1,000 simulated cohorts of new PACE enrollees of a desired size (say, 20). For each such cohort, the detailed service use histories of the individuals for the three years following enrollment are assembled and key results are summarized. These summarized values are then available for each of the 1,000 simulated groups. Means, standard deviations, and percentiles of the key results are presented in the output worksheet.

- Simulator Results

Service Categories: Eight service measurements were constructed for use in the simulator results summary. These are briefly described below.

Nursing Home	The number of days per month spent in a nursing facility.
Hospital	The number of days per month spent in a hospital.
Other Institution	The number of days per month spent in institutions other than nursing homes or hospitals (i.e. transitional housing, rehabilitation facility, psychiatric facility).

These first three service measures are derived from the inpatient stay records linked to each monthly service record. (Inpatient stay records were partitioned into calendar months and attached to the corresponding monthly service record for that individual.)

ADC Days	(MSR Attendance Days) The number of days per month spent at an adult day care center
ADC – Personal	(MSR C20 + C21) Encounter days per month at an ADC for personal care or chore services
ADC – Skilled	(MSR C10 + ... + C19 + C31 + C32) Encounter days per month at an ADC for social worker care, skilled nursing, physical therapy, occupational therapy, speech therapy, respiratory therapy, nutritional counseling, physician care, nurse practitioner care
Home – Personal	(MSR C30) Hours per month of personal care provided at home

Home – Skilled	(MSR C22 + ... + C28) Visits at home per month for physician care, nurse practitioner care, skilled nursing, physical therapy, occupational therapy, social worker services, speech therapy

In addition, we constructed an aggregate service measure (“Cost-Weighted”) by applying the following rough unit costs to six of the eight measures.

Nursing Home	$150 per day
Hospital	$1,800 per day (log-normal)
Other Institution	$300 per day
ADC Days	$50 per day
Home – Personal	$15 per hour
Home – Skilled	$100 per visit

While these costs are not completely arbitrary, they are not meant to be the most appropriate values for all situations. The simulator user can easily modify the values as needed.

While skilled care and hospital care are typically covered by Medicare and nursing home and personal care services are usually covered by Medicaid, the division of PACE services between Medicare and Medicaid is less than precise. For example, post-acute nursing home care is provided under FFS Medicare for 100 days following a hospital stay. Personal home care is provided by FFS Medicare if the individual also requires skilled care, so long as the frequency of care is not too great. Medicaid typically provides for skilled care not covered by Medicare, including co-payments and deductible payments. This makes it difficult to clearly allocate PACE services between what would have been provided by FFS Medicare versus what would have been provided under FFS Medicaid. The cost weighted service measure includes the principle components of both acute and chronic care, i.e. a combination of Medicare and Medicaid services.

Note also that the hospital cost per day is not fixed, but simulated for each individual from a log-normal distribution. The mean for the distribution decreases as the number of hospital days in the month increases. The mean structure and the variance were extracted from pre-enrollment FFS hospital claim records used in the Medicare model discussed earlier in this report.

We ran 1,000 simulated new enrollee cohorts of 20 individuals each. Records were selected from all PACE sites combined for enrollments in or prior to 1997. Services were summarized for each of three years following enrollment and for all three years combined. The following table shows the average results for the selected service measures.

Table 10: Average Service Levels by Year from Enrollment

Service	Yr 1	Yr 2	Yr 3	Yrs 1-3
Nursing Home	0.68	1.73	2.43	1.49
Other Institutions	0.29	0.29	0.24	0.28
Hospital	0.23	0.20	0.17	0.20
ADC Days	11.78	11.48	11.05	11.49
ADC - Personal	9.36	9.69	9.74	9.58
ADC - Skilled	30.95	30.30	29.14	30.27
Home - Personal	31.58	33.69	35.71	33.36
Home - Skilled	1.37	1.50	1.72	1.50
Cost-Weighted	1,748	1,862	1,950	1,839

New PACE enrollees typically do not reside in nursing homes. After enrollment, however, some enrollees migrate from a community setting into a nursing facility setting. The drop in hospitalization rates reflects survival of healthier lives and recovery from temporary acute conditions that initially require more frequent inpatient care.

In general, Medicare-type service use is likely to revert back to usual levels due to recovery from acute conditions and due to the "survival of the fittest" effect. This drop will bottom out at some point and reverse as the surviving population continues to age. Medicaid-type costs are more likely to increase continuously from enrollment as the chronic condition of the population gradually worsens with age.

The standard deviation of service use for each 20-enrollee group, expressed as a percentage of the average value, is shown in the next table.

Table 11: Service Use Standard Deviation / Expected

Service	Yr 1	Yr 2	Yr 3	Yrs 1-3
Nursing Home	105%	96%	89%	82%
Other Institutions	93%	140%	180%	100%
Hospital	65%	79%	81%	50%
ADC Days	12%	15%	18%	13%
ADC - Personal	17%	20%	24%	17%
ADC - Skilled	13%	15%	18%	13%
Home - Personal	36%	37%	41%	34%
Home - Skilled	34%	41%	45%	31%
Cost-Weighted	19%	22%	25%	17%

Despite the large relative variation in inpatient days (50% to 100%), the cost-weighted measure exhibits modest relative volatility (17%), only slightly greater than that of ADC days (13%).

Remember that the standard deviation ratios in the previous table are for enrollee groups of size 20. The ratios for other groups sizes can be estimated by multiplying by the square root of 20 and dividing by the square root of the new group size. For example, for groups of size 80, the values in the previous table should be divided by 2 (the square root of 80 divided by 20).

If we assume approximate normality, the 90%-tile of these service measures can be computed as the average plus 1.282 standard deviations. Dividing by the average service use, we obtain a loading factor such that the probability that the loaded value is exceeded by the actual value is less than or equal to 10%. The table below shows the 90% confidence loading factors for each service and enrollment year.

Table 12: Service Use 90%-tile Loading Factors

Service	Yr 1	Yr 2	Yr 3	Yrs 1-3
Nursing Home	235%	224%	214%	205%
Other Institutions	219%	279%	331%	228%
Hospital	184%	201%	204%	164%
ADC Days	115%	119%	123%	116%
ADC - Personal	122%	126%	130%	122%
ADC - Skilled	116%	119%	123%	117%
Home - Personal	146%	148%	153%	143%
Home - Skilled	144%	152%	158%	140%
Cost-Weighted	125%	128%	132%	122%

So, for cohorts of 20 new enrollees, expected costs for the first three years after enrollment must by increased by 22% to assure coverage 90% of the time. While this might be interpreted as the necessary payment loading on expected costs to assure that actual costs for the group will not exceed payments, it can also be interpreted as indicating the level of service demand for which the site should budget to avoid service access problems. Nothing in this is intended to suggest that the capitation payments from Medicare or Medicaid need to be loaded by the tabulated loading percentages.

We next consider methods available to modify the volatility of the service demand.

- It is clear that pooling experience across enrollment periods results in greater stability. While there is positive correlation between the enrollment years (roughly 42%), combining the first three years nevertheless produces a smaller relative standard deviation (and loading factor) than any of the individual years.

- Similarly, pooling the experience of one enrollment cohort with that of another, from the same PACE site or otherwise, will dampen the relative volatility of service demand and reduce the loading factor for a chosen probability of coverage. The following table shows the 75% and 90% three-year loading factors for cohorts (or combinations of cohorts) of different sizes.

Table 13: Service Use Loading Factors

	75%-tile			90%-tile		
Service	n=20	n=100	n=500	n=20	n=100	n=500
Nursing Home	155%	125%	111%	205%	147%	121%
Other Institutions	167%	130%	113%	228%	157%	126%
Hospital	134%	115%	107%	164%	129%	113%
ADC Days	109%	104%	102%	116%	107%	103%
ADC - Personal	112%	105%	102%	122%	110%	104%
ADC - Skilled	109%	104%	102%	117%	107%	103%
Home - Personal	123%	110%	105%	143%	119%	109%
Home - Skilled	121%	109%	104%	140%	118%	108%
Cost-Weighted	112%	105%	102%	122%	110%	104%

The risk reduction is more dramatic when pooling independent cohorts than when combining enrollment years within a cohort, due to the positive correlation between years from the same cohort.

- The simulated cohorts have randomly selected individuals regardless of their age, sex or health status at enrollment. Thus, some of the variation in results is due to variation in key characteristics of the enrollees from one iteration to the next. Presumably, if we require that all new enrollees share the same health status, the observed variability of service demand will be reduced. For example, if we fix the number of ADL impairments (from zero to five), then the required loading factors should shrink.

  To start, the following table shows the three-year average service demand for each ADL impairment level.

Table 14: Service Use Averages by ADL

Service	0 ADLs	1 ADL	2 ADLs	3 ADLs	4 ADLs	5 ADLs
Nursing Home	0.86	1.25	1.55	2.15	2.44	3.16
Other Institutions	0.18	0.24	0.31	0.28	0.33	0.29
Hospital	0.21	0.19	0.19	0.23	0.23	0.23
ADC Days	9.62	10.81	11.27	12.11	12.31	12.43
ADC - Personal	6.80	7.89	8.95	10.19	11.31	12.25
ADC - Skilled	25.02	29.41	29.28	30.88	33.61	32.67
Home - Personal	27.46	21.14	30.56	31.98	39.20	47.02
Home - Skilled	1.58	1.29	1.44	1.35	1.56	1.57
Cost-Weighted	1,515	1,513	1,746	1,886	2,132	2,240
Relative Index	0.823	0.823	0.949	1.026	1.159	1.218

The average values behave as expected, with chronic care (nursing home and personal care) increasing more rapidly with functional impairment than medical care (hospital and skilled care). The last row of the table shows the ADL-specific cost-weighted service demand relative to the blended value, $1,839.

For cohorts of size 20, the following table shows the standard deviation of service demand as a percentage of the expected level.

Table 15: Service Use Standard Deviation / Expected by ADLs

Service	All	0 ADLs	1 ADL	2 ADLs	3 ADLs	4 ADLs	5 ADLs
Nursing Home	82%	91%	85%	71%	67%	72%	63%
Other Institutions	100%	71%	92%	93%	70%	63%	90%
Hospital	50%	44%	43%	46%	97%	61%	54%
ADC Days	13%	12%	12%	13%	12%	12%	15%
ADC - Personal	17%	19%	18%	17%	16%	15%	16%
ADC - Skilled	13%	13%	11%	12%	12%	13%	15%
Home - Personal	34%	36%	30%	33%	34%	31%	32%
Home - Skilled	31%	31%	29%	33%	31%	32%	34%
Cost-Weighted	17%	18%	17%	17%	17%	17%	17%

It is clear that controlling for variation in ADL impairment level does little to lessen the variance of actual service demand about the expected level. The volatility of service demand from individual to individual is so great that it swamps the modest variance explained by ADL level. As the size of the new enrollment cohort increases, the individual-to-individual variance will diminish rapidly. We might anticipate that the ADL variance would then grow to become a more visible component of total volatility. However, as the cohort size increases, the impact of ADL variation will also shrink, so that its impact relative total variance will remain relatively unchanged. That is, the likelihood that the average ADL impairment count for a cohort will vary from the average for all past enrollees decreases as the cohort grows.

This would suggest that implementing ADL adjustments to the capitation structure might do little to mitigate financial risk for small cohorts. The key argument for such a refinement in rate structure is associated with non-random deviations from the average ADL impairment levels for larger cohorts. For example, if a PACE site employs different recruiting/marketing methods which result in new enrollees from a more or less impaired source population, this operational selection bias will not diminish as the site grows. An ADL-specific rate structure will adjust revenue appropriately for the biased sample.

Conclusions

After consideration of the above analyses, the following observations are offered.

Part I Observations:

1. The 1998 CHSRA analysis found that a random sample of individuals from the nursing home certifiable (NHC) population could be expected to produce FFS claim levels well below 2.39 times the average FFS claim level. It was indicated at the time that existing PACE sites had actually enrolled populations with more significant impairments than such a random sample. Part I of this analysis confirms this conjecture. Giving consideration to pre-enrollment FFS Medicare claim levels and the functional/cognitive status of actual enrollees, we estimate that FFS claims that PACE enrollees might have generated had they remained in the FFS system are consistent with an adjustment factor greater than 2.39.

2. The implied adjustment factor varies significantly from PACE site to PACE site according to the variation in pre-enrollment claims and functional/cognitive status each site's enrollees.

3. Given the pre-enrollment claim history and status at enrollment, the level of uncertainty in the estimates of the implied adjustment factors is a function of the volume of data used to fit the Medicare claims model (the 1994 NLTCS) and the number of enrollees to which the model will be applied.

4. After a period of regression to the mean, the implied frailty adjusters tend to increase gradually as the surviving enrollee cohort ages. The uncertainty in the frailty estimates also increases, but not dramatically, as the cohort matures.

5. The monthly health status transition rates act to lessen the site variation in health status over time. That is, surviving PACE enrollees from different PACE sites are expected to become more alike the longer they remain in the system. This would imply that the need for assessment of functional and cognitive status after enrollment might also diminish.

6. We find that the same factors that explain higher Medicare FFS claim levels for PACE enrollees than average Medicare enrollees, also explain the higher mortality rates for PACE enrollees. The monthly mortality rates exhibited in the DataPACE experience are consistent with the annual survival rates predicted by the NLTCS-based claim model. The Medicare claim model simultaneously predicts higher mortality and increased claim activity for PACE enrollees. Consequently, there is no need for an additional mortality-based adjustment to the payment system.

Part II Observations:

7. Actual PACE service utilization exhibits significant volatility for specific service items (e.g. hospital costs). However, the aggregate Medicare/Medicaid service demand is much more stable than its component parts. So, there does appear to be a stabilizing effect of combining Medicare and Medicaid services under a single program.

8. Allowing the adjustment factor to vary according to the enrollee's functional/cognitive status is a reasonable method of reflecting non-random site differences in the frailty level of individuals recruited into PACE. However, such a refinement will have little effect on financial risk associated with random deviations from expected results. While the risk of enrolling a small cohort with atypical characteristics is significant for small sites, this risk is dwarfed by that arising from random variation from individual to individual in actual service demand about the true expected level for each individual. For larger sites with larger enrollment cohorts, the chance of an enrollment cohort exhibiting average characteristics much different than the expected profile is diminished.

9. The most effective approach to reducing financial risk is to pool the experience of independent cohorts on enrollees. This can be accomplished by growing the site, pooling of generations of PACE enrollees over time, or more formal reinsurance schemes (pools, stop-loss, etc.). Inter-generational pooling requires some mechanism, such a reserve structure, to assure that "profits" on blocks with favorable experience are set aside to offset adverse deviations on a subsequent block.

10. While we have shown that rate loadings are necessary beyond expected levels in order to reduce the probability of revenue deficiency, the source of this loading is not necessarily the Medicare/Medicaid funding entities. For example, if PACE management wishes to keep the probability of a loss on each enrollment cohort at 75% or less, the simulator can indicate the appropriate loading factor (similar to those shown in Table 13). This loading may be funded by the PACE organization and accumulated in a contingency reserve. Alternately, the loading requirement could be commuted to a lump-sum initial surplus requirement. This minimum surplus could would be increased or released as the block grows or shrinks. Indeed, some states may require PACE programs to adhere to risk-based capital (RBC) requirements applicable to other insurance forms. RBC formulas define minimum surplus requirements which, if not satisfied, result in Insurance Department actions to restrict new issues or even replace the management team.