EXPANDED METHODS TO MODEL LAST YEAR OF LIFE EXPENDITURES IN THE MEDICARE CURRENT BENEFICIARY SURVEY WITH SENSITIVITY ANALYSES AND NEW FINDINGS

By

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ABSTRACT OF THE DISSERTATION

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Terminal year of life medical expenditures in the elderly are generally much higher than medical expenditures in other years of life. These expenditures have often been portrayed as wasteful and inefficient use of heroic procedures with little change of success at the end of life. Prior studies in this area have focused predominately on Medicare expenditures; only a handful considered overall medical expenditures. The Medicare Current Beneficiary Survey (MCBS) comprises data on all medical expenditures, not just those paid for by Medicare, but these data only include expenditures aggregated by calendar year. Thus, linear models have been applied to estimate terminal year of life medical expenditures.

This paper adds to the body of information on this topic using recent data, from the 2006-2013 MCBS. We modified previous and developed new methods to estimate end-of-life expenditures both overall and broken down by payer and service category. We also developed new sensitivity analyses to test data and model assumptions. Additionally, we compared variances of the estimates from two predominate methods for robust variance estimation in complex surveys like the MCBS, the Taylor Series

Expansion (TSE) method and Fay's modification to the Balanced Repeated Replication (BRR) method. Finally, we utilize our new method of analysis to examine univariate and multivariate covariate effects of calendar year, age, sex, race, and geographical region on selected categories of terminal year of life expenditures. This is to our knowledge, the first multivariate analysis of multivariate correlates for total end-of-life medical expenditures.

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TABLE OF CONTENTS

TABLE OF TABLES

TABLE OF FIGURES

1 SUBSTANTIVE BACKGROUND

From 2002 to 2014, the average annual total medical expenditures for an elderly American (aged 65 or older) ranged from 5.1-6.7 times that of children (aged 18 and under) and from 2.7-3.2 times that of non-elderly adults (aged 19-64) (Centers for Medicare and Medicaid Services [CMS] 2019). In 2014, the elderly made up approximately 15 percent of the US population but were responsible for more than one-third of all personal healthcare spending (CMS 2020). Overall and Medicare-paid medical expenditures for the elderly are dramatically higher in the last year of life (Scitovsky 1984; Scitovsky 1988; Lubitz and Riley 1993; Scitovsky 1994; Barnato et al 1999; Hogan et al 2001; Hoover et al 2002; Alemayehu and Warner 2004; Shugarman et al 2004; Riley and Lubitz 2010). For decades, there has been concern that a significant portion of these end-of-life expenditures for the elderly represent essentially wasted costs of heroic procedures in patients that are already known or otherwise destined to be dying soon (Scitovsky 1984; Emanuel and Emanuel 1994, Gawande, 2014).

A relatively high percentage of costs in the last year of life for the elderly are borne in the last 1 to 3 months of life (McCall 1984; Lubitz and Riley 1993; Emanuel et al 2002; Chastek et al 2012). Analysis of trends in expenditures show that the majority of all elderly Medicare population had substantial increases in costs in the last month of life, with just over 40% of this population exhibiting accelerating month-to-month medical expenditure increases over the last year of life manifesting predominately in the last 3 months prior to death (Davis et al 2016). Over the last few decades, approximately 5% of elderly Medicare beneficiaries die each year; however, in the 1990s and early 2000s the proportion of all annual elderly Medicare expenditures that are spent on the last year of life for decedents has remained stable, hovering between 25% and 31% (Lubitz and Riley 1993; Hogan et al 2001; Hoover et al 2002; Riley and Lubitz 2010).

Inpatient hospital services have comprised the largest portion of end of life expenses since at least the late 1970s, comprising between 44% to 76% of all terminal year medical expenditures (Lubitz and Riley 1993; Emanuel et al 2002; Hoover et al 2002; Riley and Lubitz 2010). However, the proportion of medical expenses spent on these services has declined over that time, both in terminal year and non-terminal year Medicare expenditures (Riley and Lubitz 2010). Instead, the proportion of end of life spending on outpatient services has seen a gradual increase over this period of time (Riley and Lubitz 2010).

Initiatives to promote the use of less expensive home health and hospice use for those near death starting in the 1990s seemed to have been successful, with dramatic rises in the portion of terminal year Medicare expenditures used on home health, hospice, and skilled nursing facilities between 1988 and 1997 (Emanuel and Emanuel 1994; Hogan et al 2001; Riley and Lubitz 2010). The proportion of Medicare spending on hospice continued to increase greatly (seemingly with the decline of home health services expenditures) from 1997 to 2006, with hospice spending reaching nearly 10% of all Medicare expenditures. Interestingly, the proportion of Medicare spending on physician and other medical services remained relatively stable over this period (Riley and Lubitz 2010).

As the percentage of the US population in the oldest age groups increases, the portion of medical expenditures spent in the end of life may expand due to increases in medical spending for patients that are more elderly and due to larger numbers of deaths amongst the elderly. But prior studies have consistently indicated that Medicare expenses in the last year of life decline with older age of death (McCall 1984; Scitovsky 1984; Lubitz and Riley 1993; Spillman and Lubitz 2000; Hoover et al 2002; Shugarman et al 2004).

Conversely, non-Medicare expenditures in the last year of life have increased with older age at death (Scitovsky 1984; Spillman and Lubitz 2000; Hoover et al 2002). Spillman and Lubitz (2000) indicate that this non-Medicare increase was largely due to increases in expenditures for long-term care facilities, which also greatly increase out-of-pocket expenses for the oldest of the elderly (Hogan et al 2001). When taking both Medicare and non-Medicare spending into account, Hoover et al (2002) found the oldest beneficiaries (those 85 and older) had the lowest overall terminal year expenditures, while the middle age group (aged 75-84) had the highest overall expenditures. However, Spillman and Lubitz (2000) found that overall end-of-life spending consistently increased with increasing age of death when looking at the last two years of life

Hogan et al (2001) found that the average Medicare outlays in the final year of life were 28% higher for minorities (i.e. mostly Black) than were those for Whites. Similarly, Shugarman et al (2004) found that mean unadjusted Medicare expenditures in the last 12 months of life were 32.5% higher for Blacks than for Whites. Additionally, unadjusted Medicare expenditures were higher for Blacks than Whites in years 2 and 3 prior to death. Women were found to have approximately 9% lower unadjusted Medicare expenditures in the year prior to death than men, though their unadjusted expenditures were higher in years 2 and 3 before death. However, in a model including age, race, sex, and income level factors, adjusted Medicare spending on Blacks was lower than Whites for each of the three years prior to death (not statistically significant in the year prior to death) and adjusted Medicare spending for men was lower than that for women for each of the three years prior to death.

As the US population ages and terminal care medical expenditures consume a huge part of the economy, evaluating the cost of dying continues to be important. While most studies have focused on Medicare costs at the end of life, few have evaluated non-Medicare expenditures, and many that have are not using data from more recent years. Such papers have been limited to only having data available for the last calendar year of life and so the data only reflects subjects' last "m" months of life where m is the difference between the date of death and December 31st of the previous year, a value between 0 and 12 months. Thus, the Hoover et. al. (2002) paper noted earlier fit the following linear model to this partial last year of life data

$$Y = \beta_0 + \beta_1\sqrt{m} + \beta_2 m + \beta_3 m^2 \qquad (1)$$

(selecting at most two of the three terms to avoid overfitting) where Y was the amount of expenditures and m was the number of months of follow-up prior to death. These authors used the Medicare Beneficiary Survey (MCBS) data (also used in this paper and described later), to estimate last year of life expenditures. It appears that many articles which emulate that approach did not perform any selection process on the model terms to avoid overfitting, as was done by Hoover et. al. (2002), but included all the terms in the model (i.e. De Nardi et al 2016, French et al 2018).

We modify, evaluate, expand, and apply the Hoover et al. (2002) approach using the MCBS data (described in Section 3 on page 10). First, the m^2 term described above was not used because it indicates expenditures decline in the last months of life which never happens and thus was not kept in any of the models in the Hoover et. al. (2002) paper. Additionally, since other studies have shown medical expenditures only increase in the very last few months of life, we considered here another term that allowed for increasing expenditures only in the last 6 months of life. Other issues arising from the coding of death dates in the MCBS in years after those used by Hoover et al (2002), that are described later in the thesis, mean that some of the models in other papers may have improper model specifications.

To summarize, as noted earlier, terminal year medical expenditures in the elderly are important because they are generally substantially higher than medical expenditures in other years of life (Hoover et al 2002, De Nardi et al 2016; French et al 2018) even in the two years prior to the terminal year of life (Shugarman et al 2004). These expenditures have often been portrayed as wasteful and inefficient due to use of heroic procedures with little change of success at the end of life (Scitovsky 1984; Fries et al 1993; Gawande, 2014). Others, however, have challenged that view saying that death is difficult to predict in all but a handful of cases and it is hard, without hindsight, to balance the costs of successful treatment with the costs of care near death (Emanuel and Emanuel 1994). Efforts to reduce wasteful spending at the end of life also cut spending on efficient medical services (Emanuel and Emanuel 1994). This paper hopes to add to the body of information on this topic using up to date data. In addition, we develop new methods for analysis of end-of-life expenditures and for evaluation of those estimates, and by doing so expand the knowledge of the techniques used in analyzing data like the MCBS.

2 OVERVIEW OF THESIS

In order to update the current understanding of these costs, this paper studies 2006-2013 Medicare and non-Medicare expenditures during the last 12 months of life using data from the MCBS. Moreover, the analytical challenge is that while terminal year costs are often of interest, for each decedent in the data set the MCBS data includes costs only by an entire calendar year. Thus except for persons who die on exactly December 31st, the exact 12-months prior to death expenditures are unknown, with some portion of these expenditures occurring in the prior calendar year. Therefore the terminal year medical expenditures must be estimated by fitting models. In this and other prior studies, this had been done by fitting models that only utilized expenditures in the calendar year of death. One issue with these models is that the estimates for expenditures in the last year of life come at the extreme high end of the data range, increasing the variability of the estimate.

Fortunately,for most decedents in the MCBS, expenditures in the calendar year prior to death are available and can easily be linked to those in the last calendar year of life. Unfortunately, those expenditures in the calendar year prior to death that occurred in the last 12 months of life cannot be separated from those that were farther out from death. Using the combined data from both years would thus have the same problem as the analysis described above, namely, terminal year medical expenditures would need to be estimated from models at the extreme end of the data range (in this case the low end). Additionally, since not all decedents in a given calendar year would have prior year data, the sample size would be lowered as compared to the analysis utilizing single calendar year data.

If we could utilize prior year data but keep our 12-month estimate in the middle of the data range, we thought that we could get lower variance estimates, despite the smaller sample size when using only decedents with prior years of MCBS data. Our solution was to add the prior calendar year data only to those decedents with less than 6 months of expenditure data (i.e. those that died in the first half of the calendar year). Therefore, this paper will also examine terminal year medical expenditures using the 2005-2013 MCBS data for beneficiaries that died in 2006-2013 and had been part of the MCBS sample for a full two years prior to death using expenditures accrued in the last 6 to 18 months prior to death. This would allow for the 12 month terminal expenditure estimate (which is of most interest to health professionals) to fall in the middle rather than the end of the range of data. Total expenditures and various subcategories of expenditures based on payer/payers or type of service will be analyzed (details on these categories are found in Section 5 on page 31).

Starting with the 1995 MCBS, the exact date of death in a month was not given, due to privacy concerns. Thus, the date of death in the MCBS data is recorded as the last day of the month (February is always coded to the 28th), which we reset to the mid-date of the month for this analysis. For example, a person who actually died on March 1st, would have a date of death of March 31st in the MCBS data, which we would reset to March 15.5th, so in months $m \approx 2.5$ rather than $m \approx 2$ (if the actual date of death was known to us) or $m \approx 3$ (based on the date given in the data) will be input into the model in (1). However, the exact dates of death are known for 1992 – 1994 MCBS. An evaluation of the impact of adjusting the death dates to the mid-date of the month versus using the real death dates on the estimates will be presented using comparative analysis on this 1992-1994 MCBS data. Other sensitivity analyses on the terms selected for in the final model for the analyses using expenditures accrued in the last 6 to 18 months prior to death will also be presented.

Many studies of complex survey data (of the type that exist in the MCBS dataset used here) relied on an approach using Taylor Series Expansion (TSE) to estimate variances for non-linear estimators. However, with increasing computing power, other robust replication techniques to create variance estimators are feasible. For the analyses in this paper, the Balanced Repeated Replication (BRR) method was primarily used instead of the TSE method as was the case for other terminal year of life expenditure studies conducted using the MCBS. A comparison of the standard errors generating using both techniques on the 0 to 12 month expenditure data and the 6 to 18 month expenditure data will be presented later.

Finally, analyses of selected expenditure categories using the last 6 to 18 month of life expenditure data will be employed to look at the multivariate effects of calendar year, age, sex, race, and geographical region, both taking each of these covariates singularly and in a multiple covariate analysis. To our knowledge this is the first such analysis of all end of life medical expenditures that has been done. The paper will discuss the implications of these findings on current and future health care costs.

3 DETAILS OF THE WORKING DATASET

The only national data set which can be used to study total end of life expenditures is the MCBS. As noted below the MCBS is a complex survey design, which requires specialized statistical methods, particularly for variance estimation. Many of the techniques available in typical probability sampling schemes (simple random sampling, stratified sampling, etc.) for estimation of variance for basic measures, such as means and regression coefficients, are intractable in such designs as these estimators are no longer linear in the data (due to the need to estimate random quantities that are fixed in other designs), and so have no closed form solutions for variance. This is very important to review here (Section 4) as it adds both constraints to how approaches must be taken as well as some of the objectives for this thesis.

3.1 Sampling structure of the MCBS

The MCBS is a continuous survey of the Medicare population, including both elderly and disabled beneficiaries. Each year of data is a stratified random sample of roughly 10,000 to 12,000 beneficiaries scientifically selected to be representative of the whole United States population of Medicare beneficiaries, both elderly (65 years and older) and disabled, enrolled in that particular year. The sampling was designed so that the beneficiaries selected from the Medicare enrollment file satisfactorily represented the entire Medicare population and each of the age groups: under 45 years (disabled), 45 to 64 years (disabled), 65 to 69 years, 70 to 74 years, 75 to 79 years, 80 to 84 years, and 85 years and over. Oversampling of groups more likely to enter long-term care facilities, such as disabled persons under 65 and those aged 80 and over, was performed so that the sample contained enough long-term facility stays for reliable estimation of these measures (CMS 2013). As such, sampling weights are necessary when calculating population estimates, since each subject represents a different number of units in the overall population.

The MCBS uses a rotating-panel design, with each panel of beneficiaries selected as described above in the fall of a given year. To be selected for a given year's panel, the beneficiary must have been enrolled in Medicare as of January 1 of that year. Each of the panels is retained for four years before being retired and replaced with a new panel of beneficiaries. Additionally, every year a supplemental sample is obtained to add newly enrolled people, account for growth in the Medicare population, and replace beneficiaries lost because of death, disenrollment, non-response, and other causes. For a given calendar year, the data from each of the panels interviewed for that year are combined to create the MCBS Access to Care and Cost and Use files. The data used in this paper comes from the Cost and Use file (described below in Section 3.2 on page 16), which includes all responding beneficiaries entitled to benefits in that year. As an example, the 2013 Cost and Use file would include selected beneficiaries enrolled in 2012 or earlier who were alive in 2013, and those newly enrolled in 2013 (CMS 2013).

For the sampling of beneficiaries, the MCBS utilizes a three-stage cluster sample design sampling from a yearly 5% sample of all Medicare beneficiaries taken by CMS (CMS 2013, CMS 2015). In the first stage of sampling, primary sampling units (PSU) consisting of major geographic areas throughout the United States, including the District of Columbia and Puerto Rico, representing metropolitan statistical areas and clusters of non-metropolitan counties, are selected for inclusion into the sample. The current set of 107 PSUs was selected in 2001 based on enrollment data from June 2000.

All 28 PSUs in the continental U.S. with at least 224,000 Medicare beneficiaries are guaranteed to be included in the sample; these 28 are denoted as *certainty* PSUs. One more certainty PSU is also included, representing the largest PSU in Puerto Rico. To select the *non-certainty* PSUs (those with less than 224,000 Medicare beneficiaries and are not guaranteed to be included in the sample), 39 sampling strata were created (38 in the continental US, 1 in Puerto Rico) and then from all PSUs only two PSUs are selected PPS from each of these strata. The sampling strata were created by first grouping PSUs by census region and Metropolitan Statistical Area status. Then, the PSUs in each of these groups were sorted by HMO enrollment proportion and, in some cases, minority percentages. Based on this sorting, strata were created of roughly equal size (CMS 2013, CMS 2015).

For the years used in this analysis, the next stage of the process involved selecting secondary sampling units (SSUs) based on ZIP Codes and ZIP Code Fragments located within the PSUs using a systemic probability proportional to size method. For the non-certainty PSUs, a fixed number (up to a maximum of 6) of SSUs were selected, while for the certainty PSUs, an even number of SSUs were selected, subject to a minimum of 6 (CMS 2013, CMS 2015). For the last stage of this process, beneficiaries are selected within each of the SSUs.

Because the BRR method of variance estimation relies on a selection (as described below in Section 4.2 on page 21), of exactly two PSUs within a sampling strata a bit of tweaking was done by the MCBS designers in order to generate the replicate weights used for the BRR. Therefore, they created 100 “variance strata”, each with two “variance units”, and 100 BRR replicate weights were created by utilizing these “variance strata” as the sampling strata and the “variance units” as the PSUs in the BRR method. Thirty-nine of these variance strata were simply the 39 primary sampling strata used for the non-certainty PSUs. Because two non-certainty PSUs were selected from each of these strata, those PSUs selected translate directly to the variance units for those strata. The remaining 61 BRR variance strata were created from the 29 certainty PSUs. Within each of these PSUs, SSUs were grouped into 61 variance strata each containing 2, 4, or 6 SSUs. These strata comprised all the SSUs within the PSU and did not cross PSU boundaries. Inside each of these strata, two variance units were created by randomly grouping 1, 2, or 3 SSUs (for strata containing 2, 4, or 6, SSUs respectively) for 1 of the variance units and using the other 1, 2, or 3 SSUs for the other (CMS, email message to author, April 15, 2019).

Because of the oversampling of beneficiaries from certain groups (and therefore undersampling of beneficiaries from other groups), the rotating-panel design, and unequal selection probabilities for the PSUs and SSUs, it would be inappropriate to analyze these data as if all sample observations were independently selected with equal probability. Instead design-based analyses are needed to compute appropriate estimates of means and totals, and their estimates of variance. To do this, weights must be determined for each beneficiary included in the final sample.

In an informal sense, the weight for a unit in a sample is the number of units in the overall population represented by that sample unit. However, the initial sample in the

MCBS is not a representative sample and so CMS performs several steps in order to develop the final sample weights in the MCBS. As in most complex surveys, a base weight is computed for each sample beneficiary that is the inverse of the inclusion probability of that beneficiary in the sample. Since sampling is done in multiple steps, the inclusion probability for a beneficiary for a given calendar year's panel, is the product of the probability of being in the yearly 5% sample of all Medicare beneficiaries, the probability of selection of their PSU, the conditional probability of selection of their SSU within that PSU, and finally their conditional probability of selection within that SSU (CMS 2015).

These base weights are then further adjusted for subject nonresponse and for demographic differences between the sample and the original population. First, the weights are adjusted for nonresponse probability based on the demographic characteristics of the population (CMS 2015). Typically, in a complex survey like the MCBS, this would often be done by way of poststratification, but this process requires knowledge of the distribution (or at least good estimates) of these characteristics in the overall population (Lee and Forthofer 2006, Wolter 2007). However, in the MCBS, these characteristics are not known, so instead the weights are adjusted using an iterative process called *raking*. Weights are iteratively adjusted to match the control totals in each of four raking dimensions (age group × sex × race, census region × age group, metropolitan status × age group, and the year of enrollment in Medicare). Then, a nonresponse adjustment must be made since a significant number of beneficiaries selected for inclusion into the MCBS do not respond to an interview. The weights so determined are the final weights for each calendar year's panel.

As a final step, since the MCBS is a rotating-panel design, in a given calendar year, the sample consists of beneficiaries from four panels, one for the current year (the process described above) and three representing the prior three years. For those beneficiaries selected in one of the three prior years' panels, the weights for the current year are adjusted for additional nonresponse (for the current year) starting with the previously adjusted weights from the prior year (so if current year is 2013, using the 2012 weights). These adjusted weights for the prior years' panels are combined with those of the current year. These weights are then adjusted to account for quadruple coverage, triple coverage, and double coverage of those beneficiaries added to the MCBS three years, two years, and one year prior to the current year. These weights are the final continuously-enrolled cross-sectional weights found in each calendar year's survey file provided by CMS (CMS 2015).

The 100 BRR replicate weights, used for variance estimation, for the current year's panel were derived from the initial base weights using Fay's method with $\tau = 0.3$ as described below in Section 4.2 (page 21) (CMS 2013, CMS 2015). The replicate weights were then tweaked in the same manner as the initial base weights, first by applying the raking procedure, adjusting for nonresponse, and finally by adjusting for the rotating-panel design (CMS 2015). -

Because the panels described above are rotated out every four years, weights are not just created for those beneficiaries contained in a given calendar year's data, but are also created for analyses that require samples of beneficiaries that have been a part of the MCBS over multiple years. From 2006-2013, the Cost and Use files contained 3 sets of 101 weights (a single sample weight and 100 BRR replicate weights): cross-sectional weights for the single calendar year's data , 2-year weights for those beneficiaries in the current year's sample that were added in the panels selected two or three years prior to the current year (as an example, for 2009, any MCBS-enrolled beneficiary that was added in the 2007 or 2006 panels), and 3-year weights for those beneficiaries in the current year's sample that were added in the panel selected three years prior to the current year (as an example, for 2009, any MCBS-enrolled beneficiary that was added in the 2006 panel). These multi-year weights for a given calendar year are constructed from the weights described above after the adjustments for nonresponse in all prior year panels. The 2-year weights are then adjusted for double coverage of those added to the MCBS 3 years prior to the current year using compositing factors derived in a similar fashion as for the cross-sectional weights. The 3-year weights are unadjusted in this fashion because only one panel provides the data for this population (CMS 2015).

3.2 MCBS data collection and the Cost and Use file

Sampled beneficiaries, or their proxies, are interviewed three times a year (approximately every four months) over four years. Two different interview processes are used depending on whether the sampled person resides in the community or in a long-term care facility. These interviews assess all health care encounters for a given beneficiary. In the community interviews, accuracy is improved by asking responders to save and submit Explanation of Benefit forms from Medicare, statements from private health insurers, and receipts from providers. Additionally, survey participants are asked to bring medication containers for all prescriptions to the interview to help ensure accurate reporting of prescription medications. Most of these interviews are conducted with the sampled person directly, but in case the person is unable to answer the questions (for example a decedent), a proxy is designated. In the facility interviews, a similar, but shorter interview is used. Moreover, due to health issues often present in institutionalized patients that prevent these persons from being directly interviewed, information on these patients are collected from various proxy respondents. For example, questions on physical functioning and medical treatment are typically garnered from nurses and/or primary care givers, while people from the billing office respond to questions related to charges, payments, and sources of payment (CMS 2013).

The Cost and Use file utilized in these analyses does not solely rely on MCBS survey data. Instead it utilizes the survey reported data from the MCBS merged with data from Medicare claims and from other administrative files from the Centers for Medicare and Medicaid Services. The survey reported data includes information on the use and costs of health care services, particularly those health services not covered by Medicare or Medicaid and long-term facility care. It additionally provides information on supplementary insurance and demographics. The Medicare bill data contains cost and use information on inpatient and outpatient care, medical provider services, prescription drugs, home health services, hospice services, skilled nursing home services, and other medical services (CMS 2013).

Since Medicare covered services are reported in both the Medicare billing system and the MCBS survey, the overlap between the two is used to assess the accuracy of the survey reports. All beneficiary-reported services were compared with the corresponding information from the Medicare billing system in order to adjust the survey-reported expenditures by accounting for any discrepancies or unreported payments found in those bills submitted and paid by Medicare. Typically, inconsistencies between beneficiary reports and the Medicare billing system have been due to surveyed beneficiaries under-reporting expenditures relative to the associated Medicare bills. Minor expenses and routine care, in turn, predominately accounted for these under-reported costs. In addition to cross-checking survey reported data with Medicare billing, for payment amounts where the information from Medicare could not be used for correction, an imputation process was used to fill in estimated payments (CMS 2013).

4 VARIANCE ESTIMATION

This paper aims to estimate medical expenditures in the last 12 months preceding death. As the MCBS is released every calendar year, for decedents in a given calendar year expenditure data covers only the entire amount of time that they were alive in that year not the entire last 12 months of their life. Therefore, in order to estimate the expenditures in the last year of life, a model (as described in (1) and below) incorporating the time alive must be fit, and then an estimate of expenditures can be calculated by plugging in a full year into that model of the form $Y = \beta X$ where β is a vector of parameters estimated from the data and X is a matrix with the rows representing functions of how many months the patient survived in the last calendar year of life. The goal is to estimate βX for a person who has 12 months of information prior to death. These estimates can also be used for other time periods such as the last 3 or 6 months of life. While these estimates themselves can be relatively easy to compute, issues can arise when the variances of those estimators are desired for confidence bands or prediction intervals. For linear estimators, this is not a problem; however, in complex survey designs, like the MCBS, estimates for the regression coefficients for these models are nonlinear (unlike in a simple random sample), and so exact expressions for their sampling variances or even simple, unbiased estimators of these variances rarely exist (Rust 1985; Potter et al. 2003; Wolter 2007).

Two classes of techniques have been developed to obtain these variance estimates. The first class consists of a single method, the Taylor Series Expansion (TSE) linearization approach. The other class of variance estimation techniques consists of replication methods where replicate weights are computed for the data and are used to calculate new estimates of the estimator in question (Rust 1985; Rust and Rao 1996; Lee and Forthofer 2006; Wolter 2007). These replicate estimates can then be used to obtain a variance estimate for $\hat{\beta}$ and $\hat{\beta}X$ the non-linear estimator. One of the most, if not the most, commonly used of these replication techniques is known as Balanced Repeated Replication (BRR) which derives replicate weights using balanced half-samples of the original sample. In the traditional BRR method, half of the information contained in a full sample is not used for each of the replicate weights. To preserve the full sample information for each replicate weight, the BRR is often modified with a technique known as Fay's method (Rust 1985; Potter et al. 2003; Lee and Forthofer 2006; Wolter 2007; Chowdhury 2013). The MCBS data allows for use of either the TSE or BRR with Fay's method approaches.

4.1 Taylor Series Expansion method

While both replication and linearization approaches have been around for many decades, traditionally, the TSE linearization approach has been more often used for variance estimation of complex survey designs such as MCBS as the BRR replication approaches require a large amount of computing power to be done successfully. The idea behind the TSE approach is to approximate the nonlinear estimator desired, $\hat{\theta}$, with a linear estimator by deriving the first-order Taylor series expansion about the parameter θ. Variance estimates can then be computed using the standard formulas of variance estimation for linear estimators, which may involve unknown parameters which must then be estimated from the data in the sample.

Because these variance estimators are based upon linear forms of nonlinear estimators, a certain amount of bias will be introduced, but typically, they will be consistent. Additionally, since, normally, the nonlinear estimator, $\hat{\theta}$, whose variance is desired will be biased for the parameter of interest, θ, the TSE variance estimators will actually estimate the mean square error for $\hat{\theta}$. A major advantage of this approach is that for complex, multistage surveys, like the MCBS, only estimates of PSU totals are needed for variance estimation (assuming with replacement sampling), greatly reducing computational complexity (Rust 1985, Potter et al 2003, Lee and Forthofer 2006, Wolter 2007, Chowdhury 2013).

4.2 Balanced Repeated Replication method

As mentioned above, the other way of variance estimation in complex, multistage designs involves replication methods. The idea with these methods is to draw multiple subsamples from the full sample and estimate the parameters of interest using these subsamples. The variances of the parameters are then estimated using the variability amongst these estimates (SAS Institute Inc. 2009). The method used for the MCBS is the BRR method with the addition of an adjustment known as Fay's method (CMS 2013, CMS 2015).

To explain further, consider the problem of estimating the variance for some linear estimator, $\hat{\theta}$, (since the variance, $v(\hat{\theta})$, has a simple form) from a complex, multistage design like the MCBS. For simplicity, suppose further, that we have a design where exactly two PSUs are selected by a probability proportionate to size (PPS) with replacement for each of I strata. One way to estimate $v(\hat{\theta})$ is to split our sample into two independent half-samples (or replicates) by choosing exactly one PSU per stratum for the first half-sample, putting the complementary PSU from that stratum into the other half sample, and doubling the weights, W_{ijk} (where i represents the strata, j the PSU within that strata, and k the unit within that PSU), for each unit. Putting this another way, we can form each replicate by assigning a new weight, where for each half-sample α,

$$W_{ijk}^{(\alpha)} = \begin{cases} 2W_{ijk}, \text{ if PSU } j \text{ in stratum } i \text{ is in the half-sample (replicate)} \\ 0, \text{ otherwise.} \end{cases}$$

We can then create the following variance estimator

$$v_R(\hat{\theta}) = \frac{\left(\hat{\theta}^{(1)} - \hat{\theta}\right)^2 + \left(\hat{\theta}^{(2)} - \hat{\theta}\right)^2}{2}$$

where $\hat{\theta}^{(1)}$ is the estimate from the first half-sample, and $\hat{\theta}^{(2)}$ is the estimate from the complementary half-sample.

Unfortunately, while $v_R(\hat{\theta})$ is computationally simple, because it is based on a single degree of freedom it will often have too high a variance to be of any practical use. Instead we would like to create another variance estimator that has the computational simplicity of $v_R(\hat{\theta})$ but with lower variance. The BRR technique provides an estimator that satisfies these conditions by repeating this process of forming half sample replicates using different combinations of units from each stratum and using these replicates to estimate the variance. However, these half-sample replicates will have some dependence between them because some units will be held in common between replicates, unless the inclusion of units can be balanced in some way (Rust and Rao 1996, Lee and Forthofer 2006, Wolter 2007).

To do this, consider the process by which we constructed the first half-sample replicate above, where we selected exactly one unit from each of the I strata. Because we can choose one of two PSUs per stratum and with I strata, there are exactly 2^I such half-samples that can be formed, each with a corresponding estimator $\hat{\theta}^{(\alpha)}$. Now, since each unit in the full sample is member of exactly half of the possible half-samples, that is in 2^{I-1}, half samples , we have that the mean of the $\hat{\theta}^{(\alpha)}$ is equal to $\hat{\theta}$ (Wolter 2007).

If we repeat the process of taking half-samples L times, we can construct the following variance estimator based on our estimators $\hat{\theta}^{(\alpha)}$

$$v_L(\hat{\theta}) = \sum_{\alpha=1}^{L} \frac{\left(\hat{\theta}^{(\alpha)} - \hat{\theta}\right)^2}{L}$$

Because each of the $\left(\hat{\theta}^{(\alpha)} - \hat{\theta}\right)^2$ is unbiased for $v(\hat{\theta})$, then so must be $v_L(\hat{\theta})$. However, cross-stratum terms in $v_L(\hat{\theta})$ may introduce additional variance in this estimator above that of $v(\hat{\theta})$. We would like to find a way to pick half-samples such that $v_L(\hat{\theta}) = v(\hat{\theta})$. If we define

$$\delta_i^{(\alpha)} = \begin{cases} 1, \text{ if PSU } (i,1) \text{ is in the } \alpha\text{-th half-sample} \\ -1, \text{ if PSU } (i,2) \text{ is in the } \alpha\text{-th half-sample.} \end{cases}$$

then because

$$\sum_{\alpha=1}^{2^I} \delta_i^{(\alpha)} \delta_{i'}^{(\alpha)} = 0,$$

then the mean of the $\left(\hat{\theta}^{(\alpha)} - \hat{\theta}\right)^2$ taken over all 2^I half-samples is exactly $v(\hat{\theta})$ due to the cancelling out of all the cross-stratum terms (Wolter 2007)

However, when the number of strata, I, is large, as is often the case in complex, multistage survey designs like the MCBS, taking the mean of the $\left(\hat{\theta}^{(\alpha)} - \hat{\theta}\right)^2$ over all 2^I half-samples becomes computationally impractical. Instead we might consider computing this mean over a much smaller subset of these half-sample replicates. If we could find a way to eliminate those cross-stratum terms by carefully choosing our subset of half-samples, we can get that $v_L(\hat{\theta}) = v(\hat{\theta})$ and so ensure that $Var\left(v_L(\hat{\theta})\right) = Var\left(v(\hat{\theta})\right)$. A sufficient condition to achieve this is if we can select a subset of replicates with the property that

$$\sum_{\alpha=1}^{L} \delta_i^{(\alpha)} \delta_{i'}^{(\alpha)} = 0$$

for all $i \neq i'; i, i' = 1, \ldots, I$. A set of with such a property is referred to as balanced (Rust 1985, Rust and Rao 1996, Wolter 2007).

Fortunately, such balanced subsets can be created using a method developed by Plackett and Burman (1946) to construct matrices called Hadamard matrices. These matrices are $L \times L$ orthogonal matrices, with order 1, 2, or a multiple of 4, with entries equal to either -1 or +1. If we associate the strata with the columns in these matrices, the rows with the half-sample replicates, and the entries in the (α, i)-th cell corresponding to $\delta_i^{(\alpha)}$ then the columns satisfy the above equation. An example of an 8x8 Hadamard matrix is given below.

	Stratum							
Replicate	1	2	3	4	5	6	7	8
1	-1	+1	-1	+1	-1	+1	-1	+1
2	+1	-1	-1	+1	+1	-1	-1	+1
3	-1	-1	+1	+1	-1	-1	+1	+1
4	+1	+1	+1	-1	-1	-1	-1	+1
5	-1	+1	-1	-1	+1	-1	+1	+1
6	+1	-1	-1	-1	-1	+1	+1	+1
7	-1	-1	+1	-1	+1	+1	-1	+1
8	+1	+1	+1	+1	+1	+1	+1	+1

Given I strata, then all we need to do is pick a value L, the smallest multiple of 4 greater than or equal to I, and then using a Hadamard matrix of dimension L pick any set of I columns to define a set of L balanced replicates (Rust and Rao 1996, Wolter 2007).

It is often useful in the case where I is a multiple of four to take L to be the next higher multiple of four, rather than I, so that the average of our replicate estimates, $\hat{\theta}^{(\alpha)}$, will equal $\hat{\theta}$. As can be seen in the example given above, the last column contains a +1 for each row, implying that the first PSU from the 8th stratum will be selected in each half-sample. Since all Hadamard matrices contain a column with either all +1's or -1's (all other columns have an equal number of +1's and -1's), then if $L = I$, the mean of the $\hat{\theta}^{(\alpha)}$ will not be equal to $\hat{\theta}$, since the latter includes both PSUs from the stratum associated with this column while the former will only include one. In this case, taking $L = I + 4$, and taking any of the $I + 3$ columns other than the column with all +1's or -1's, we achieve both this property and balance, with only a slight additional computational burden (because we use $I + 4$ replicates instead of I replicates) (Wolter 2007).

We can now generalize this variance estimator to more complicated sample estimators using the previous formula. For any sample estimator $\hat{\theta}$, the BRR variance estimator is given by

$$v_{\mathrm{BRR}}(\hat{\theta}) = \sum_{\alpha=1}^{L} \frac{\left(\hat{\theta}^{(\alpha)} - \hat{\theta}\right)^2}{L},$$

for a set of $L \geq I$ balanced half-sample replicates. For linear estimators, because the BRR variance estimator does not differ from the standard form, there is little reason to use BRR. The real utility in BRR comes when used for nonlinear estimators (including those made in this paper), where often no simple, unbiased variance estimators exist. Because the BRR provides an unbiased estimate with decent precision for linear estimators, it is assumed that BRR will provide a variance estimator of reasonable bias and adequate precision for nonlinear estimators. Numerical studies have suggested that this is indeed so (Rust 1985, Rust and Rao 1996, Lee and Forthofer 2006, Wolter 2007).

We noted above that this technique creates new weights for the sample values based on the selection of the half-samples in each replicate. Namely, each value y_{ijk} in the sample gets a replicate weight, $W_{ijk}^{(\alpha)}$, of either 0, if the PSU it is contained in is not selected for that replicate, or $2W_{ijk}$, if the PSU it is contained in is selected for that replicate. This means that information from values not contained in each half-sample are thrown out when computing the estimate for that replicate. Instead of completely discarding this information, a variant to the BRR, known as Fay's method, changes these replicate weights to utilize all values. In this method, the half-samples are defined in the same way as in the standard BRR. However, the weights are adjusted based on a value $\tau, 0 \leq \tau < 1$ as follows:

$$W_{ijk}^{(\alpha)} = \begin{cases} (2-\tau)W_{ijk}, & \text{if the } i\text{-th PSU is "included" in replicate } \alpha \\ \tau W_{ijk}, & \text{otherwise} \end{cases}$$

Note that for $\tau = 0$, these replicate weights will correspond to the original BRR method. The variance estimator is then given by

$$v_{\text{FAY}}(\hat{\theta}) = \sum_{\alpha=1}^{L} \frac{\left(\hat{\theta}^{(\alpha)} - \hat{\theta}\right)^2}{(1-\tau)^2 L}.$$

As with the original BRR method, for a linear estimator, $\hat{\theta}$, $v_{\text{FAY}}(\hat{\theta}) = v_{\text{BRR}}(\hat{\theta}) = v(\hat{\theta})$. Similarly, there will be slight, but acceptable, discrepancies for nonlinear estimators (Judkins 1990, Rust and Rao 1996, Lee and Forthofer 2006). Korn and Graubard (1999) found that for $\tau = 0.3$, Fay's method produced similar results as the standard BRR with smaller variance when the replicate weights were adjusted to account for non-response and poststratification.

4.3 Comparison of TSE and BRR methods

In the prior two sections, we reviewed the two methods available to estimate the variances needed to fit the models needed for this paper, the TSE method and the BRR with Fay's method. Since both methods use the same point estimate (these methods are only used to estimate variance) and both methods produce robust, and therefore, conservative, estimates of variance, other considerations are needed to determine the best approach for a particular set of complex survey data and the estimator one wishes to analyze.

The BRR method has several advantages over the TSE method. First, the TSE method relies on easily obtainable linear forms for non-linear estimators, but these do not exist or are difficult to calculate for many complex estimators (Rust 1985; Paben 1999;

Potter et al. 2003; Wolter 2007; Chowdhary 2013). Additionally, the TSE method assumes that the only non-trivial contribution to the variance of the desired estimator comes from the first order term in the Taylor series expansion and all other terms beyond this are relatively insignificant (Rust 1985; Wolter 2007; Chowdhary 2013).

The BRR method does not have these shortcomings, as it solely relies on replicating the original estimate using balanced half-sample replicates which allows its use with any complex estimator, regardless of its Taylor series expansion. Second, any non-response, poststratification, and raking adjustments made to the original survey base weights can be used on the replicate weights derived using BRR to account for variance due to these adjustments on the base weight. The linear forms derived in the TSE method are typically derived for the base estimator without capturing the effect of any of the weighting adjustments on the base estimator. Finally, once BRR replicate weights are calculated for the data, subdomain analyses are quick and easy, and do not require the full data to produce accurate variance estimates, while the TSE method always requires the full set of data when an estimator for a subpopulation is desired.

Reviews of Monte Carlo studies applying both methods to various sets of data have also indicated that the BRR method have the best confidence coverage interval properties of all variance estimation techniques, often considered the most important single criterion, though actual confidence interval coverage probabilities of all of the available methods (including the BRR) tend to be lower than the nominal probability. Additionally, these studies indicated that for multiple correlation coefficients the BRR method may outperform the TSE method when considering the mean square error (MSE), despite the TSE generally outperforming the BRR for simple survey statistics. TSE does seem to have the advantage over the BRR when it comes to bias considerations; however, the patterns seen in these studies were generally not clear nor consistent (Wolter 2007).

One other advantage of the TSE method is that it is much easier for non-technical investigators to apply as replicate weights need not be computed. Additionally, deriving the replicate weights in the BRR method is computationally intensive, especially if those replicate weights are adjusted for raking and non-response. These limitations can be partially overcome for many investigators if these weights are computed by the data holders (as is done with the MCBS); however, setting up the model incorporating the weighted replicates remains a challenge.

To date, no analysis to compare the TSE and BRR methods has been done using the MCBS data. Moreover, few examples of comparisons between these two methods exist in the literature for other data. However, an analysis using data from the Medical Expenditure Panel Survey (MEPS) from the Agency for Healthcare Research and Quality by Chowdhury in 2013 aimed to compare the TSE and BRR methods for variance estimation. The variance estimates for various proportions and means for selected variables were derived using both the TSE and Fay's BRR methods. The author computed these variance estimates starting from the initial base weights and proceeding through various nonresponse and raking adjustments to the final full year weights.

For the final full year weights (equivalent to the weights given in the MCBS), variance estimates for the BRR were 5-10% lower than the variances computed using TSE for most estimates, and for some estimates the BRR variances compared to the TSE variances were lower than that. However, in this analysis, a handful of estimates showed the opposite, with TSE variances lower than those derived using the BRR. Reductions in variance using the BRR method were related to the correlation between the variable analyzed and the variables used in the various raking adjustments, with higher correlations leading to lower variance estimates using BRR. Additionally, the BRR variances were typically higher than those produced with the TSE method in the presence of outliers. Removal of these outliers prior to analysis resulted in the same general pattern of lower variance estimates using the BRR versus the TSE method.

All prior analyses of end-of-life medical expenditures using the MCBS such as Hoover et al in 2002 have used the TSE method for variance estimation or do not report variances (De Nardi et al 2016, French et al 2018). As guided by CMS, the main analyses done in this paper were all done using Fay's BRR method with a Fay's perturbation factor of 0.3. However, since comparisons of these two variance estimation methods have never been made using the MCBS data, and little exists in the statistical literature to compare these two approaches, it became one of the goals of this thesis to empirically evaluate the differences between the BRR method and the TSE method when estimating end-of-life medical expenditures using the MCBS.

5 SPECIFIC MCBS MEASURES USED IN THE ANALYSES

The MCBS data was described earlier; now we focus on the specific MCBS measures used for this analysis. The MCBS Cost and Use data sets contain 21 variables for calendar year medical expenditures. In addition to a total medical expenditure variable, they include two separate breakdowns of the total medical expenditures.

The first partition of the expenses breakdown the total amount paid on medical expenditures on behalf of each beneficiary by 11 different payers. These payer variables are *Medicare fee-for-service* (excludes amounts paid by Medicare-funded Health Maintenance Organizations [HMO]), *Medicaid* (including copayments and deductibles paid to Medicare), *Private HMO* (includes all amounts paid by private insurance based HMOs, regardless of purchaser of insurance)*, Medicare HMO, Veterans' Administration* (VA), *Private Insurance (employer-sponsored)* (excludes employer-sponsored private HMO coverage), *Private Insurance (self-purchased)* (excludes self-purchased private HMO coverage), *Private Insurance (unknown)* (accounts for all non-HMO private insurance where the purchaser of the insurance [employer or self] was unknown), *Out-of-pocket* (all expenses paid for by the beneficiary directly [including co-payments, deductibles, and payments made by family members or others for the patient]), *Discounted Amount* (uncollected liabilities, those unpaid amounts with a legal obligation to pay), and *Other Public* (any Federal, State, or local healthcare programs not included in any other category).

To facilitate analysis, certain payor variables were combined into new values. The following expenditure categories were analyzed. *Total Medical Expenditures*: all medical expenditures regardless of source or service. *Medicare*: all costs paid for by Medicare, including both Medicare fee-for-service and Medicare-funded HMOs. *Non-Medicare*: All other expenses paid by any source other than Medicare (includes the Discounted Amount category). *Total private*: all medical expenditures paid by private sources, includes private HMO, private insurance (regardless of purchaser), and out-of-pocket expenditures. *Total public*: all expenditures paid for by any governmental source, includes Medicare (both fee-for-service and Medicare-funded HMO), Medicaid, VA, and other public expenditures. Additionally, some of the costs borne by these sources were analyzed separately: *Out-of-pocket, Medicaid,* and *Private Insurance* (all payments by private insurers either employer-based or self-purchased, including payments to private HMOs).

Expenses paid by the VA, all other public health plans, and all uncollected liabilities were included in the analysis of the overall total and non-Medicare categories, but were not analyzed separately, due to the limited number of beneficiaries with non-zero values for expenditures in these categories. Total payments made by HMOs, both Medicare-funded (included in the Medicare and total public categories) and privately funded (included in the non-Medicare, total private, and private insurance categories), were combined and analyzed as a distinct category.

The second breakdown of medical expenditures in the MCBS is by service category. Expenditures were analyzed separately for each service category: *dental services, facility* (licensed/skilled nursing homes, retirement homes, hospital long-term-care units, intermediate care facilities, domiciliary facilities, assisted/foster care homes, and mental health/developmentally-disabled care facilities), *home health care, hospice* *care, inpatient hospital*, *institutional events* (includes all short-term stays [admission and discharge in the same year] in long-term-care facilities), *medical provider* (payments to physicians or other clinicians providing medical care), *outpatient hospital*, and *prescribed medicine* (excludes payments for medicine prescribed in inpatient or facility settings which were included in those categories).

For each year, all expenditure categories were adjusted for inflation to 2013 dollars using the Bureau of Labor Statistics consumer price index (CPI) (United States Bureau of Labor Statistics 2020). For example, for an expenditure category in 2008, this was done using the formula:

$$\frac{\text{CPI in 2013}}{\text{CPI in 2008}} \times \text{2008 US dollar value} = \text{2013 US dollar value.}$$

Whenever the actual date of death was known (in the 1992-1994 MCBS data), in order to account for the fact that a beneficiary could have died at any time on that day, it was assumed that a decedent had died at 12pm on the day of death. For example, a beneficiary dying on January 5th would have the number of days alive in that year set to 4.5.

However, one issue found in the MCBS data, starting in the year 1995, is that respondent's death dates have been masked due to privacy concerns, and are set to the last day of the month and year of death (or February 28th for those dying in the February of a leap year). As obtaining these dates would have been both time- and cost-prohibitive, all death dates were set to the midpoint of the month, assuming a relatively uniform distribution of deaths given the month of death. For example, a beneficiary dying in June would have the number of days alive in a given year set to the number of days between January 1st and June 15th for that year (the 15 would be used because $\frac{0.5+29.5}{2} = 15$, 0.5 is for June 1st, 29.5 for June 30th, as noted in the previous paragraph). A beneficiary dying in July, would have the number of days alive in a given year set to the number of days between January 1st and July 15th for that year, plus an additional half day to account for the 31 day month. For a patient dying in February, the adjustment was made according to whether the year was a leap year or not, going from January 1st to February 14th, plus an additional half day to account for a 29 day month if the year was a leap year.

For the 1992-1994 sensitivity analysis, since the actual dates of death were known for most beneficiaries, in order to account for the time of death on the day of death, 0.5 was subtracted from the number of days alive (thus putting all deaths at noon of the given day). That is, if a beneficiary died on Jan 2nd, the number of days alive would be set to 1.5. This adjustment is also reflected in the setting of death dates to the midpoint of each month. The number of months alive was then calculated using the formula: $\frac{\text{days alive}}{365.25} \times 12 = \text{months alive}$.

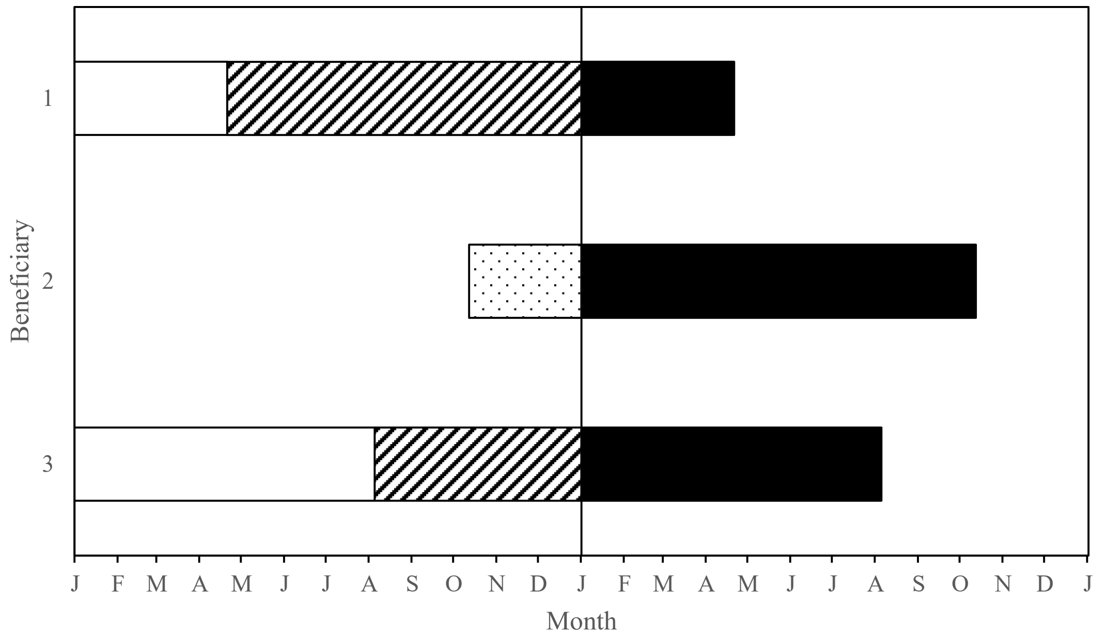
Additional variables used in this paper from the MCBS data included calendar year of death, age category (65-69, 70-74, 75-79, 80-84, and 85+ years), sex, U.S. Census region (Midwest, Northeast, South, West, and Puerto Rico), and race.

6 ESTIMATION OF TERMINAL YEAR EXPENDITURES

Terminal year expenditures were defined as those expenses for respondents who died 12 or fewer months after the expense date. As mentioned earlier, MCBS expenditures are recorded by calendar year rather than on a daily or monthly basis. This is the main statistical challenge in estimating the terminal year expenditures from these data, since we only observe expenditures for the portion of the calendar year in which the given person was alive, rather than the full 12 months of life prior to the given respondent's death.

For example, consider the MCBS expenditures for three beneficiaries all dying in 2007: Beneficiary 1 who died on April 21, 2007, with full calendar year MCBS data for the previous 3 years (2004-2006); Beneficiary 2 who died on October 12, 2007, without having previously been a part of the MCBS sample; and Beneficiary 3, who died August 5, 2007, with a prior 2 full years of MCBS data (2005-2006). For Beneficiary 1, the 2007 MCBS would only have expenses for the last nearly 4 months of life which were incurred in 2007, while those incurred in the last 5 to 12 months prior to death would be in the 2006 MCBS (Beneficiary 3 would be similar to 1, but with a different time frame). For Beneficiary 2, the 2007 MCBS would contain the only data available for this beneficiary and would only cover the expenditures incurred in the last approximately 9 and a half months prior to death, with expenditures incurred in the last 2 and a half months of 2006 totally unavailable. This is shown in Figure 1 below, with black representing the data from the year of death (2007), white representing data from the prior year outside of the terminal year, white with black lines representing data from the prior year within the terminal year, and white with black dots representing unavailable data within the terminal year.

Figure 1. Timelines and available data for theoretical decedent beneficiaries from the 2007 MCBS



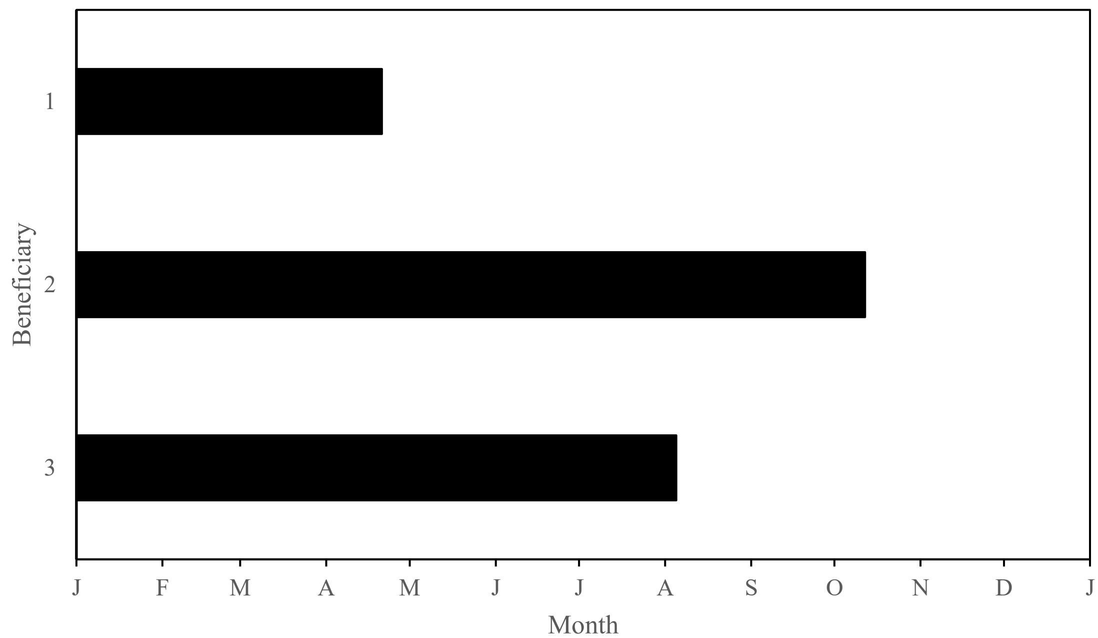
Theoretical beneficiaries dying April 21, October 12, and August 5, 2007. Solid black represents the data available for the year of death. White represents prior year data (2006) outside of the last 12 months of life. White with black lines represents prior year data within the last 12 months of life whose data is available only in combination with the data in white to the left. White with black dots represents time within the last 12 months of life where data is unavailable.

6.1 Methods

6.1.1 Using expenditures over the last 12 months of life

Because of the lumping of data by calendar year, two analyses were done to estimate mean expenditures for the last 12 months of life. The first, called the *0-12 month analysis*, used only data from the given calendar year a person died as had been done in prior studies (Hoover et al 2002, De Nardi et al 2016, French et al. 2018). Continuing with the three theoretical beneficiaries in Figure 1 above, the data used for these patients is shown in Figure 2, below. The standard, single-year cross sectional sample and BRR replicate weights described in the previous sections were used for analyzing these data. As mentioned earlier, all expenditure values were adjusted to 2013 dollars. Following this adjustment, data from the years 2006 to 2013 were pooled (these years were used to facilitate comparison with the 6-18 month analysis described in the next section).

Figure 2. Data used for theoretical decedent beneficiaries from the 2007 MCBS for the 0-12 month analysis



Theoretical beneficiaries dying April 21, October 12, and August 5, 2007. Black represents the pre-death time period for which data is available and used for these beneficiaries for the 0-12 month analysis of terminal year expenditures.

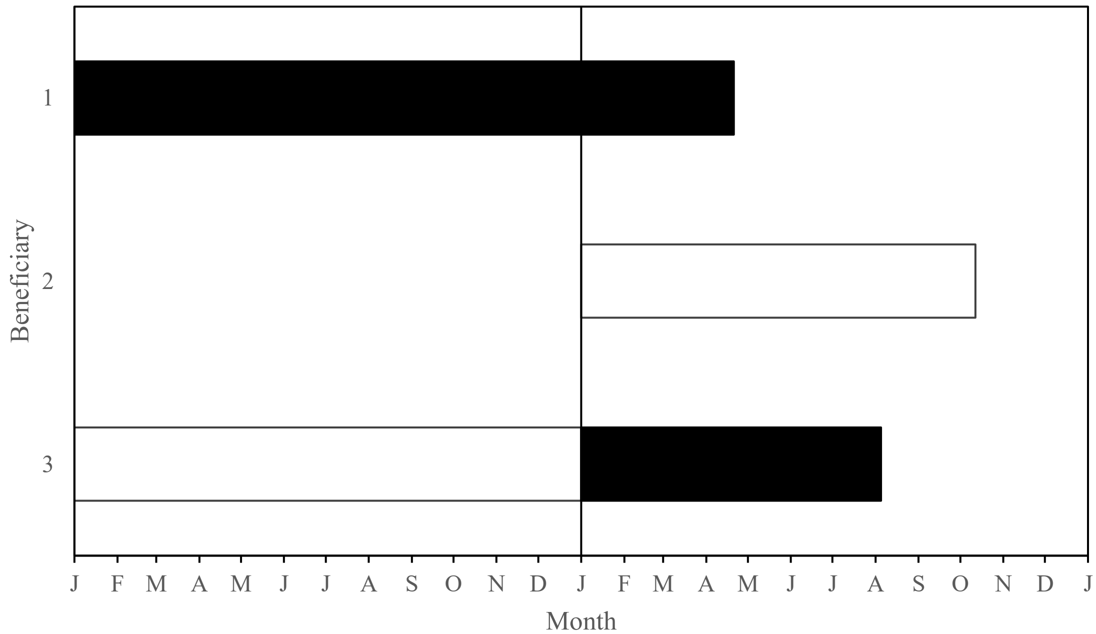
For the 0-12 month analysis, mean expenditures in the last year of life was modeled with linear polynomial models using BRR with a Fay's coefficient of 0.3 starting with 4 terms: $Y = \beta_0 + \beta_1\sqrt{m} + \beta_2\sqrt{\min(m, 6)} + \beta_3 m$, where Y is the expense of interest and m is the number of months of follow-up based on the number of days alive in the calendar year of death using the midpoint of the month of death expressed in months as described in Section 5. Least significant terms were removed by backward selection until all terms were significant at $p < 0.05$. If, however, both the $\sqrt{m}$ and $\sqrt{\min(m, 6)}$ terms were in the final model, the backward selection was re-run after first eliminating the least significant of these two terms (in all the cases where both were significant the coefficients for these terms had opposite signs and were essentially cancelling each other out). Removal of terms stopped when a model was reduced to the point of having only one non-intercept term. These models represent the average trend of spending in the last year of life. To estimate average terminal year expenditures, point estimates and confidence intervals were calculated from the coefficient estimates and their covariances by setting $m = 12$. Note that due to differences in model selection, the sums of estimates of mutually exclusive and exhaustive measures within a larger category are not necessarily equal to the estimate in that larger category (eg, the total expenditures estimate may not be equal to the sum of the Medicare and non-Medicare expenditure estimates), but the differences were minor.

6.1.2 Using expenditures over the last 6 to 18 months of life

One disadvantage with the previous approach is that the terminal year estimate at 12 months is at the end of the range of data. To counter this disadvantage, at the cost of sample size, a second previously unused method was developed. This second method, called the *6-18 month analysis*, used data from those beneficiaries that were a part of the MCBS for the given year and the prior two years, so a 2007 MCBS respondent who died in 2007 would also have MCBS data from 2005 and 2006 (while it would have been preferable to have used those who were part of the MCBS for the given year and the prior year, survey weights and replicate weights prior to 2015 were only available for respondents having three consecutive years of MCBS data). For this analysis, patients who died in the first half of a given year (those who had 0-6 months of expenses in the given year) had the expenses from the prior year added to the given year to give these respondents 12-18 months of expenditure data, while only the given year data was used for those who died in the second half of the year (those who had 6-12 months of expenses in the given year).

Using the three theoretical beneficiaries dying in 2007 given in Figure 1, this would mean that Beneficiary 2 would be excluded from this analysis as data was only available from 2007 and so would not have the needed sample and replicate weights for this analysis as noted below. Beneficiary 1, dying with less than 6 months of data in the 2007 MCBS would have the expenditure data from the 2006 MCBS added to their 2007 MCBS data, while Beneficiary 3, dying with more than 6 months of data in the 2007 MCBS would not have the 2006 MCBS expenditure data added to their 2007 MCBS data. This use of data is shown in Figure 3, below.

Figure 3. Data used for theoretical decedent beneficiaries from the 2007 MCBS for the 6-18 month analysis



Theoretical beneficiaries dying April 21, October 12, and August 5, 2007. Beneficiaries 1 and 3 had at least prior 2 years of MCBS data, beneficiary 2 was a new MCBS subject. Black represents the data available and used for these beneficiaries for the 6-18 month analysis of terminal year expenditures. White represents the data available but not used for the 6-18 month analysis of terminal year expenditures.

The black bars in the above figure represent the data used for this analysis, with the white bars representing data available but not used for analysis. This analysis utilized the 2-year longitudinal sample and BRR replicate weights for all analyses. To do a proper comparison between these two different methods of obtaining terminal expenditures, it was decided to utilize the same years of beneficiary data. Because the 2-year sample and BRR replicate weights were not available until 2006, both these analyses used the 2006-2013 MCBS Cost and Use files for selection of included beneficiaries. In the 6-18 month analysis, data from the 2005 MCBS Cost and Use file were used for those beneficiaries dying in the first half of 2006 as described above. All expenditure values were adjusted to 2013 dollars prior to combination. Data from the years 2006 to 2013 were pooled for model fitting.

For the 6-18 month analysis, mean expenditures for the last 12 months of life was modeled with linear polynomial models using BRR with a Fay's coefficient of 0.3 with 3 terms: $Y = \beta_0 + \beta_1\sqrt{m} + \beta_2 m$, where Y is the expense of interest and m is the number of months of follow-up based on the number of days alive in the calendar year of death and the year prior for those who died in June or earlier of the calendar year of death using the midpoint of the month. Least significant terms (excluding the intercept) were removed by backward selection until all terms were significant at $p < 0.05$. Removal of terms stopped when a model was reduced to the point of having only one non-intercept term.

To estimate average terminal year expenditures point estimates and confidence intervals were calculated from the coefficient estimates and their covariances by setting $m = 12$. Again, note that as with the 0 – 12 month models due to differences in model selection, the sums of estimates of mutually exclusive and exhaustive measures within a larger category are not necessarily equal to the estimate in that larger category (eg, the total expenditures estimate may not be equal to the sum of the Medicare and non-Medicare expenditure estimates). Due to the range of data used in this analysis, the models derived in this analysis do not fully represent trends in expenditures in the final year of life, but rather in the 6-18 months of life prior to death.

6.1.3 Comparison of estimates from 0-12 month and 6-18 months analyses to each other

In order to compare the terminal year expenditure estimates for each expenditure category coming from the 0-12 month analysis and the 6-18 month analysis, three ratios were calculated. The first gives a way to directly compare the point estimates of terminal year expenditures from each of the two models developed in the 0-12 and 6-18 month analyses. For each expenditure category, the ratio of the point estimate from the 6-18 month analysis with the estimate from the 0-12 month analysis was computed, that is, $\frac{\text{12-month point estimate, 6-18 month analysis}}{\text{12-month point estimate, 0-12 month analysis}}$. The other two ratios were designed to compare the variability in the point estimates from the 0-12 month and 6-18 month analyses. The first of these is a simple ratio of the standard error (SE) of the 12-month point estimate from the 6-18 month analysis (SE_{6-18}) with the standard error of the 12-month point estimate from the 0-12 month (SE_{0-12}) analysis, that is, $\frac{SE_{6-18}}{SE_{0-12}}$. The second of these, which we call the efficiency ratio, adjusts for the smaller sample size in the 6-18 month analysis (which required the subjects to have MCBS data from the 2 calendar years prior to the calendar year of death) as compared to the 0-12 month analysis (which only required availability of MCBS data in the calendar year of death). This value is computed from the prior ratio of the standard errors, multiplied by the square root of the ratio of the sample size for the 6-18 month analysis (n_{6-18}) with the sample size for the 0-12 month analysis (n_{0-12}), that is, $\frac{SE_{6\text{-}18}}{SE_{0\text{-}12}} \times \sqrt{\frac{n_{6\text{-}18}}{n_{0\text{-}12}}}$.

6.2 Demographics for 0-12 month and 6-18 month analyses

The demographics on sex, race, age category, and US Census region for the samples of decedent beneficiaries used in the 0-12 month and 6-18 month analyses are noted below in Table 1. The population records for each of the analyses shows that these populations are comparable on the basis of sex, race, age group, and US Census region. Since the sample used in the 6-18 month analysis is a subset of that used in the 0-12 month analysis (it excludes all those decedents without at least 2 prior years of MCBS data), this shows that those patients excluded from the 6-18 month analysis (but included in the 0-12 analyses) are reasonably similar to those included in the 6-18 months analysis.

Table 1. Demographics for decedent beneficiaries used in the 0-12 and 6-18 month analyses for MCBS years 2006-2013

	Analysis	
	0-12 Month	6-18 Month[a]
Total decedent beneficiary records, n	4274	2626
Sex, n (%)		
Female	2384 (55.8)	1450 (55.2)
Male	1890 (44.2)	1176 (44.8)
Race, n (%)		
White	3664 (85.7)	2243 (85.4)
Black	421 (9.9)	266 (10.1)
Hispanic	85 (2.0)	53 (2.0)
Asian	39 (0.9)	25 (1.0)
North American Native	21 (0.5)	13 (0.5)
Other	36 (0.8)	21 (0.8)
Unknown	8 (0.2)	5 (0.2)
Age category, n (%)		
65-69	325 (7.6)	159 (6.1)
70-74	346 (8.1)	212 (8.1)
75-79	595 (13.9)	363 (13.8)
80-84	928 (21.7)	576 (21.9)
85+	2080 (48.7)	1316 (50.1)
US Census region, n (%)		
Midwest	1019 (23.8)	613 (23.3)
Northeast	805 (18.8)	508 (19.4)
Puerto Rico	58 (1.4)	37 (1.4)
South	1639 (38.4)	1020 (38.8)
West	753 (17.6)	448 (17.1)
Calendar year, n (%)		
2006	627 (14.7)	390 (12.9)
2007	574 (13.4)	343 (13.1)
2008	549 (12.9)	343 (13.1)
2009	485 (11.4)	337 (12.8)
2010	536 (12.5)	304 (11.6)
2011	498 (11.7)	299 (11.4)
2012	497 (11.6)	310 (11.8)
2013	508 (11.9)	300 (11.4)

a The 6-18 month sample of decedents is wholly contained in the 0-12 month sample. This sample excludes all decendent beneficiaries without at least 2 years of MCBS data prior to the year of death.

Sample weighted means and standard deviations of last calendar year of life medical expenditures for decedents in each expenditure category as well as the average duration of backwards follow-up from death (i.e. number of months lived during last calendar year of life) for the two samples of decedent beneficiaries for the 0-12 and 6-18 month analyses are given in Table 2. Note that these expenditure values are based on the entire duration of backwards follow-up for that analysis (in 2013 dollars), hence the values for the 6-18 month analyses being higher than the equivalent for 0-12 months

Table 2. Mean (SEM)[a] for death backwards follow-up duration and unadjusted expenditures by category

	Analysis	
	0-12 Month	6-18 Month
Duration of follow-up, months	5.77 (0.07)	12.06 (0.07)
Expenditures[b,c]		
Total	42905 (742.1)	67902 (1463.2)
By payer		
Medicare	30006 (651.6)	44647 (1253.2)
Non-Medicare	12899 (287.0)	23255 (536.0)
Total private	7856 (228.7)	13696 (417.1)
Total public	34678 (696.9)	53653 (1360.5)
Out-of-pocket	5465 (178.0)	9829 (371.6)
Medicaid	3843 (141.3)	7757 (337.5)
Private insurance	2392 (114.7)	3867 (203.4)
Total HMO	2000 (161.2)	3324 (270.9)
By service		
Dental	64.53 (8.85)	177.4 (23.16)
Facility	7286 (219.4)	13697 (465.5)
Home health	1254 (66.26)	2140 (144.5)
Hospice	3113 (118.3)	4400 (240.5)
Inpatient hospital	17441 (519.6)	23807 (916.8)
Institutional	3826 (164.1)	6203 (259.4)
Medical provider	6031 (167.8)	10115 (376.1)
Outpatient hospital	2322 (125.4)	4141 (254.7)
Prescribed medicine	1568 (58.63)	3222 (116.4)

a SEMs estimated using BRR with Fay's method
b Values are given in 2013 dollars
c Expenditure means and SDs are computed based on total follow-up time used in these analyses, that is from 0-12 months and 6-18 months, resulting in the higher values for the 6-18 month analysis

6.3 Results for 0-12 month analysis

For each of the eighteen categories of expenditures the parameter estimates and their 95% confidence intervals for the final selected model (as described in Section 6.1.1 on page 36) using the 0-12 month data can be found in Table 3, below. Note that in the 0-12 month analysis (unlike the 6-18 month analysis), the intercept was allowed to drop out of the model during backwards selection.

For all expenditure classifications, graphs of the curve for the selected models for each category over the last year of life are depicted in Figure 4 through Figure 21 found in Section 12.1.1 starting on page 138. Each graph includes the estimated curve with 95% confidence bands and the weight-adjusted mean cumulative expenditures from January 1st of the year of death through the date of death for all included decedent beneficiaries by month of death (January, February, ….., December). These figures are organized such that the total expenditure category is first, followed by expenditure categories based on the payer of services, followed by those categories based on the type of service involved in the expenditure, as in Table 3, below.

Table 3. Parameter estimates (95% CI) for model terms in 0-12 month analysis

	Parameter included in final model			
	Intercept	Months	$\sqrt{\text{Months}}$	$\sqrt{\min(\text{Months},6)}$
Total	–	–	19089 (18467, 19710)	–
By payer				
Medicare	–	–	13091 (12529, 13652)	–
Non-Medicare	–	1679.3 (1433.4, 1925.2)	–	1602.8 (913.1, 2292.5)
Total private	–	746.0 (495.9, 996.0)	1575.0 (935.3, 2214.8)	–
Total public	–	–	15294 (14689, 15898)	–
Out-of-pocket	–	687.9 (471.6, 904.3)	657.1 (145.4, 1168.8)	–
Medicaid	–	660.0 (602.5, 717.6)	–	–
Private insurance	–	170.4 (67.67, 273.0)	–	708.3 (393.1, 1023.4)
Total HMO	–	–	873.0 (729.2, 1016.7)	–
By service				
Dental	–	11.99 (8.42, 15.57)	–	–
Facility	–	1258.1 (1170.9, 1345.2)	–	–
Home health	–	104.0 (29.60, 178.5)	–	326.5 (128.1, 524.9)
Hospice	–	–	1403.9 (1299.9, 1507.9)	–
Inpatient hospital	6989.3 (4246.2, 9732.4)	–	4630.6 (3333.9, 5927.4)	–
Institutional	–	303.7 (192.8, 414.6)	–	1050.2 (718.8, 1381.7)
Medical provider	–	–	2707.6 (2566.2, 2849.0)	–
Outpatient hospital	–	238.4 (129.4, 347.4)	–	490.8 (161.6, 820.0)
Prescribed medicine	-565.0 (-970.5, -159.6)	156.6 (76.41, 236.8)	–	614.0 (176.2, 1051.7)

Cells without an estimate indicate that parameter was not selected in the final model. Note that unlike the 6-18 month analysis, the intercept was allowed to drop out during backwards selection.

6.3.1 Presentation of models by terms included

As can be seen in Table 3, we can separate the models selected across all 18 expenditure categories into four different classifications based on the terms included in each model: i) model has a linear term in months only, ii) model has a square root term in months only (with or without a non-zero intercept), iii) model has both linear and square root terms in months, and iv) model has both a linear term and a square root term in months for the 6 months prior to death (with or without a non-zero intercept). Note that the intercept was not dropped during backwards selection, even if it was not significant.

For the linear only term models, the model fit for each expenditure category was $Y = \beta_1 m$. The linear term in the model indicates that the expenditures tended to accumulate constantly over time in the last year of life.

Selection of the square root term only model implies that the rate of medical expenditures starts increasing at 12 months prior to death with these rates of increase accelerating right up until death. This suggests that most of the expenditures in the terminal year of life occurred in the final few months of life. For example, the expenditures between 9 months and 4 months prior to death are the same as in the last month of life ($\beta_1(\sqrt{9} - \sqrt{4}) = \beta_1$). For these all but one expenditure category was fit without intercept resulting in a final model of $Y = \beta_1\sqrt{m}$, with the remaining category, inpatient hospital, having a final model of $Y = \beta_0 + \beta_1\sqrt{m}$. Since the intercept in this case is positive, this implies that there is a large bolus of expenditures within the last few days or weeks of life, unaccounted for by the square root term in the model.

Of note is that for inpatient hospital expenditures, the initial backwards selection process resulted in a model that included both the $\sqrt{\min(m, 6)}$ term and the $\sqrt{m}$ terms, with the parameter estimates for these terms having opposite sign. As discussed in Section 6.1.1 (page 36), the selection process was re-run, but with the least significant of these two terms dropped first before proceeding with standard backwards selection. This eliminated the $\sqrt{\min(m,6)}$ term (the $\sqrt{m}$ was significant in the initial model, while the $\sqrt{\min(m,6)}$ was not).

All expenditure categories where the final selected model contained both the linear and square root in months terms had final models of $Y = \beta_1 m + \beta_2\sqrt{m}$, where both coefficients were positive. As in the prior set of models that included the square root term alone, the inclusion of this term, with positive sign, indicates that there is an acceleration in the increase in expenditures as a beneficiary gets closer to death. However, because of the additional inclusion of the linear term, the acceleration is relatively slower over the course of the terminal year than if it had only included the $\sqrt{m}$ term , with a larger portion of expenditures taken on further from death than would be indicated with a square root term alone.

In the final classification, where the final selected model contained both a linear term and a square root term in months for the 6 months prior to death, the final model was either $Y = \beta_1 m + \beta_2\sqrt{\min(m,6)}$ or $Y = \beta_0 + \beta_1 m + \beta_2\sqrt{\min(m,6)}$. In all these expenditure categories, both non-intercept terms had positive coefficients. As in the prior set of models that included both the linear and square root terms in months for the whole of the terminal year, having a positive linear and positive $\sqrt{\min(m,6)}$ term in the model shows that there is a slow acceleration in the increase in expenditures closer to death, but only starting at approximately 6 months prior to death, rather than starting all the way back at 12 months prior to death. Beyond this period (i.e. 7-12 months prior to death), increases in expenditures are relatively constant over time.

In one case, prescribed medicine, the model contains a negative intercept. This negative intercept would imply a smaller increase immediately prior to death than would otherwise be given by the model without taking this term into account. This may be a result of this model being complicated by the fact that it does not include expenditures for all prescription medicine. For example, any medicines given in a hospital setting will be counted under the appropriate category, inpatient or outpatient hospital expenditures.

Table 4 presents each of these potential models with the list of expenditure categories (indicating significant intercepts where necessary) where that model was selected. Additionally, it gives a short interpretation of the growth in expenditures by time in the last year of life for each of those 4 models.

Table 4. Final selected models for expenditure categories in the 0-12 month analyses with interpretation of model

Final model selected	Expenditure categories	Interpretation of model
Linear in months term only	• Medicaid • Dental • Facility	Constant increase in expenditures over the last year of life
Square root in months term only	• Total • Medicare • Total public • Total HMO • Hospice • Inpatient hospital[a] • Medical provider	Accelerating increase in expenditures over the last year of life, most accumulation in last months of life
Linear and square root in months terms	• Total private • Out-of-pocket	Accelerating increase in expenditures over the last year of life, but not as fast as with square root term alone.
Linear in months and $\sqrt{\min(m, 6)}$ terms	• Non-Medicare • Private insurance • Home health • Institutional • Outpatient hospital • Prescribed medicine[b]	Constant increase in expenditures 7 to 12 months from death, with accelerating increase from 0-6 months from death.

a Final selected model for this expenditure category had a significant positive intercept
b Final selected model for this expenditure category had a significant negative intercept

6.3.2 Further interpretation of included terms in by-service categories

As described in the previous section , the models developed in the 0-12 month analysis not only provide a means to estimate terminal year medical expenditures, but can also be used to see general trends in the timing of the accumulation of these expenditures in the last year of life. Since trends in the total and by payer expenditure category depend on the services utilized, we first examine these trends in the by service categories.

Increases in most medical expenditures in the service categories accelerate as one approaches death, as might be expected due to increasing illness in the time closer to death. As seen in Table 4, these increases are particularly dramatic for inpatient hospital, hospice, and medical provider expenditures, since these categories have a sole square root term in the model. Use of this model for hospice services is unsurprising since these services are used when death is known or suspected to be imminent. For medical provider and inpatient hospital services, this accelerating increase may point to heroic attempts to save life near death. For inpatient hospital services the additional significant large positive intercept bolsters this potential, as this would indicate significant expenditures in the last few weeks of life.

The models for home health, outpatient, and prescribed medicine also indicate an accelerating increase in expenditures in the last 6 months of life, but with steady costs further out from death. The steady costs in the last 7-12 months of life likely point to regular utilization of these services (e.g. dialysis for outpatient services or regular prescription medications), followed by the acceleration increase in the last 6 months of life due to increasing sickness. However, this slow acceleration does not necessarily point to heroic efforts to save life.

Institutional expenditures have the same pattern as seen in home health, outpatient hospital, and prescribed medicine expenditures. However, in the MCBS, this category accounts for planned short term stays (less than a year) at long-term care facilities. As can be seen in Figure 18, the monthly means in months further from death are farther from the curve than in the first four months. The larger variability further out from death may reflect that many decedent beneficiaries are utilizing these services only in the last few months of life so that even amongst those with longer follow-up, the expenditures for the calendar year only cover part of that time. This would also explain the selection of the linear and square root up to 6 months prior to death model, since there would not be as many additional expenditures, overall, on these services added in the months further out from death.

In contrast to the institutional expenditure category, the facility expenditure category reflects expected long-term stays in long-term care facilities. It is unsurprising that a linear model was selected for this category as these expenditures are likely mostly fixed month-to-month costs, similar to other housing payments like rents, and would be relatively unaffected by increasing sickness near the end of life. This conclusion is made more compelling by the strong clustering of the month to month means on the predicted regression line as seen in Figure 14.

For terminal year dental expenditures, there is quite a bit of variability in the month to month means relative to the regression equation (Figure 13), particularly in those months further from death, making this model hard to interpret. A possible explanation for the higher level of monthly expenditures seen in the means of those with approximately 10, 11, and 12 months of data relative to the monthly expenditure trend seen in those with less than 6 months of data could be that, due to more serious illness closer to death and the typical biannual dental checkup schedule, there is an decreased likelihood of recent dental visits in the latter group.

6.3.3 Interpretation of included terms in by-payer categories

In order to evaluate the trends seen in the by payer expenditure categories, a way to breakdown expenditures by service and by payer is necessary. Since the MCBS does not provide these breakdowns, we relied on the National Health Expenditure (NHE) data also compiled by CMS, which assesses annual medical expenditure in the U.S. by service, payer, and sponsor (businesses, households, or government). While these data tally all personal health care spending for those 65 and older, not just that of decedents, it serves as a reasonable basis for considering the expenditure pattern for terminal year expenditures based on service and payer, especially in light of the significant spending done on decedents (Lubitz and Riley 1993; Hogan et al 2001; Hoover et al 2002; Riley and Lubitz 2010). For this paper, we utilized the historical data, for the years 2006, 2008, 2010, and 2012 (releases for these breakdowns are given in even years).

The NHE data showed that, for those 65 and older, hospital and medical provider services were the largest components of Medicare expenditures on personal health care. Hospital services accounted for approximately 44% to 48% and medical providers 27% to 28 of total annual Medicare expenditures on personal health care for those 65 and older (CMS 2018). As seen in the 0-12 month analysis, the inpatient hospital and medical provider models fit the Medicare model well, with all three using the square root term in the 0-12 month. Despite a slightly different model in the 0-12 month analysis (which includes the linear and $\sqrt{\min{(m, 6)}}$ terms), outpatient hospital expenditures may also be a factor in the overall Medicare model. Additionally, since Medicare terminal year spending makes up most of total and public spending, respectively, 68.6% and 85.6%, (based on the terminal year estimates of $45347 for Medicare expenditures divided by the total estimate of $66,125 and the total public estimate of $52,978, respectively, shown in Table 7 for the 0-12 month analysis), it is likely that these expenditure categories are also driving the patterns seen in total and total public terminal year expenditures.

The historical NHE data reveals, as is probably well known, that the predominate portion of Medicaid spending categories for those 65 and older are long term care facilities (43%-49% of total Medicaid spending) (CMS 2018). Since these expenditures for long-term care facilities are similar to housing costs, and therefore, relatively fixed month-to-month costs, it is unsurprising that the model for Medicaid in the 0-12 month analyses is linear in months with no intercept term, similar to the facility category.

For terminal year out-of-pocket expenses, the model selected for the 0-12 month analyses includes both the linear and square root terms in months. This pattern indicates a source of steady out-of-pocket expenses coupled with a source of spending with an accelerating increase as one approaches death. The NHE data indicates that, from 2006-2012, annual out-of-pocket expenditures in those 65 and older, the major spending categories are long term care facilities (26%-29%), non-durable medical products (19%) (these products include non-prescription drugs and medical sundries), medical provider (13%-15%), and prescription drugs (13%-15%) (CMS 2018). Since terminal year expenditure estimates for prescription drugs were relatively low, these were not likely to be major factors in terminal year out-of-pocket spending patterns.

However, the 0-12 month models do find that the facility expenditure model is linear in months (with no other terms) and the medical provider expenditure model contains the square root in months term (again with no other terms). This would fit the pattern mentioned above, with a steady source of spending in the time leading up to death coming from long-term care facility expenditures, and accelerating costs prior to death for medical providers. Based on the terminal year estimate for out-of-pocket expenditures of $10,531 and the estimate of total private expenditures of $14,408 (shown in Table 7 for the 0-12 month analysis), approximately 73% of last year of life private expenditures are out-of-pocket, and so the pattern seen in the total private expenditure category is driven by out-of-pocket expenditures.

The 0-12 month model for terminal year private insurance includes both the linear term in months and the $\sqrt{\min{(m, 6)}}$ term. Private insurance spending in those 65 and older for the years 2006-2012 predominately focused on hospital services (34%-36%), medical provider services (26%-28%), and prescription drugs (17-19%) according to the NHE data (CMS 2018). The model selected for terminal year private insurance expenditures, thusly loosely corresponds to the models for the inpatient hospital (square root term with intercept), outpatient hospital (linear and $\sqrt{\min{(m, 6)}}$ terms), medical provider (square root term), and prescription drug expenditure (linear and $\sqrt{\min{(m, 6)}}$ terms with intercept) categories that indicate acceleration in these costs prior to death in at least the last 6 months.

The NHE data shows that in those 65 and older that annual private insurance spending is approximately 12% of the total and 20% of that of Medicare on hospital services, 17% of the total on medical providers, and 24% of the total on prescription drugs (CMS 2018). Based on these percentages and the model selected for private insurance and the four service categories of inpatient, outpatient, medical provider, and prescription drugs, it seems likely that terminal year private insurance spending may be driven more by outpatient services versus inpatient services and the model of prescription drugs than is seen for total and Medicare terminal medical expenditures, since the models for outpatient hospital and prescription drugs include the linear term in months and the $\sqrt{\min{(m, 6)}}$ term.

For all non-Medicare terminal year expenditures, the final model selected included the linear term in months and the $\sqrt{\min{(m, 6)}}$ term. Since the major contributors to this category were, in order from largest to smallest of dollar amounts contributed, out-of-pocket, Medicaid, and private insurance and all of these categories contained a linear term, with out-of-pocket having a square root term and private insurance with a $\sqrt{\min{(m, 6)}}$ term, this model seems to fit these categories.

6.4 Results from 6-18 month analysis

As explained earlier, due to the terminal year estimate falling at the edge of the range of follow-up time in the 0-12 month analysis, we performed a similar analysis as in the 0-12 month analysis by restricting it to those decedent beneficiaries with at least 3 calendar years of MCBS data (the two years prior to the year of death and the year of death). In order to make the 12-month estimate fall in the middle of the range of data, those decedents with less than 6 months of follow-up in the calendar year of death had the prior year's MCBS data (after adjustment for inflation) added to that of the year of death, while those with at least 6 months of follow-up were left as is. Because all patients had at least 6 months of data, the model fitting procedure did not consider the $\sqrt{\min{(m, 6)}}$ term when fitting the model. Additionally, to account for different expenditure patterns in the 6 months prior to death, the intercept was retained for all models. For each of the eighteen categories of expenditures the parameter estimates and their 95% confidence intervals for the final selected model (as described in Section 6.1.2

on page 38) for each category of expenditure using the 6-18 month data can be found in Table 5, below.

For all expenditure classifications, graphs of the curve for the selected models for each category over the 6 to 18 months of life are depicted in Figure 22 through Figure 39 found in Section 12.1.2 starting on page 147. Each graph includes the estimated curve with 95% confidence bands and the weight-adjusted means for all included beneficiaries that died in each month (with the points located at the mid-point of that month). These figures are organized such that the total expenditure category is first, followed by expenditure categories based on the payer of services, followed by those categories based on the type of service involved in the expenditure, as in Table 5, below.

Table 5. Parameter estimates (95% CI) for model terms in 6-18 month analysis

	Parameter		
	Intercept	Months	$\sqrt{\text{Months}}$
Total	17243.4 (6601.1, 27885.8)	4201.8 (3254.6, 5149.0)	–
By payer			
Medicare	10621.3 (1539.8, 19702.9)	2822.2 (2001.4, 3643.0)	–
Non-Medicare	-8864.5 (-16041.9, -1687.0)	–	9350.6 (7157.5, 11543.8)
Total private	-3955.4 (-9339.1, 1428.3)	–	5138.7 (3487.6, 6789.7)
Total public	12352.4 (2560.6, 22144.2)	3425.6 (2537.6, 4313.7)	–
Out-of-pocket	-3836.2 (-7909.7, 237.4)	–	3978.2 (2691.2, 5265.2)
Medicaid	-4719.1 (-8937.7, -500.4)	–	3632.1 (2299.4, 4964.9)
Private insurance	1779.8 (364.4, 3195.3)	173.1 (51.9, 294.3)	–
Total HMO	523.1 (-2151.2, 3197.4)	–	815.3 (17.9, 1612.8)
By service			
Dental	-269.5 (-452.0, -87.0)	–	130.1 (72.7, 187.5)
Facility	-5574.2 (-11716.2, 567.9)	–	5610.1 (3668.0, 7552.2)
Home health	-1264.4 (-2515.9, -13.0)	–	991.0 (602.8, 1379.3)
Hospice	299.3 (-2358.0, 2956.5)	–	1193.9 (362.3, 2025.5)
Inpatient hospital	6723.6 (776.2, 12670.9)	1417.0 (869.1, 1964.8)	–
Institutional	4009.3 (1357.1, 6661.5)	181.9 (-39.9, 403.8)	–
Medical provider	359.1 (-2064.2, 2782.4)	809.2 (574.2, 1044.2)	–
Outpatient hospital	-71.0 (-1522.8, 1380.7)	349.3 (209.9, 488.7)	–
Prescribed medicine	15769.7 (1153.6, 30385.9)	1701.3 (465.2, 2937.5)	-9624.2 (-18163.1, -1085.4)

Cells without an estimate indicate that parameter was not selected in the final model.

6.4.1 Presentation of models by terms included

Similarly to the models selected in the 0-12 month analysis, for the 6-18 month analysis we can separate the 18 expenditure categories into different classifications based on the non-intercept terms selected for the model. Three categories occurred: i) model had linear term in months only (i.e. final model of $Y = \beta_0 + \beta_1 m$), ii) model had square root term in months only (i.e. final model of $Y = \beta_0 + \beta_1 \sqrt{m}$), and iii) model had both linear and square root terms in months (i.e. final model of $Y = \beta_0 + \beta_1 m + \beta_2 \sqrt{m}$). Since most expenditures occur at the very end of life (i.e. the last 6 months of life), the pattern of terms in these models is not as informative as those in the 0-12 month analysis.

Table 6 presents each of these potential models with the list of expenditure categories where that model was selected. Additionally, it indicates if the intercept was positive or negative and whether it was significantly different from 0. It also gives a short interpretation of the growth in expenditures by time in the last 6 to 18 months of life for each of model.

Table 6. Final selected models for expenditure categories in the 0-12 month analyses with interpretation of model

Final model selected	Expenditure categories	Interpretation of model
Linear in months term only	• Total[a,c] • Medicare[a,c] • Total public[a,c] • Private insurance[a,c] • Inpatient hospital[a,c] • Institutional[a,c] • Medical provider[a] • Outpatient hospital[b]	Constant increase in expenditures over the last 6 to 18 months of life
Square root in months term only	• Non-Medicare[b,c] • Total private[b] • Out-of-pocket[b] • Medicaid[b,c] • Total HMO[a] • Dental[b,c] • Facility[b] • Home health[b,c] • Hospice[a]	Accelerating increase in expenditures over the last 6 to 18 months of life
Linear and square root in months terms	• Prescribed medicine[a,c]	Accelerating increase in expenditures over last 6 to 18 months of life, but not as fast as with square root term alone.

a Final selected model for this expenditure category had a positive intercept
b Final selected model for this expenditure category had a negative intercept
c Intercept in final selected model for this expenditure category was statistically significant at the 0.05 level

Of note is that for the linear only models, all significant intercepts were positive. These significant positive intercepts could indicate an increase in the rate of accumulation of expenditures in the 6 months prior to death, as the models selected for these categories in the 0-12 month analysis contained one of the two square root terms in months (either for the full 12 months or just the 6 months prior to death).

For institutional expenditures, only the intercept term was significant. But as described in Section 6.1.2 (page 38), at least one of the non-intercept terms is always kept in the final model, with the linear term in months having a lower observed significance level than the square root term, resulting in the months (p=0.11) and intercept (p=0.0034) terms used for the final model. Since these are short-term stays (less than one year), it is possible that most people utilize these services only within the last 6 months of life, and so the consistent average cost of these expenditures in the last 6-18 months of life may be because so few additional expenditures accrue in this time frame.

In the square root only models, the significant intercepts were all negative. These may signify that the acceleration of expenditures on the on the square root scale in the 6-18 month analysis slows down on that scale when moving beyond the range to closer than 6 months before death.

Only one expenditure category, prescribed medicine, had both a linear and square root term in months (with a significant positive intercept). As seen in Table 5, the linear term has a positive coefficient, while the square root term has a negative coefficient. Taken at face value, this would imply that in the range 6 to 18 months from death the rate of increase in prescription medicine expenditures decreases as one approaches death. However, since at the 6 month end of the range, the model is not monotonically increasing, this model is difficult to interpret. It is possible that the breakdown in this model is due to missing costs found in other measures, like inpatient hospital expenditures.

6.5 Estimates of medical expenditures in the last year of life from the 0-12 and 6-18 month analyses

Estimates for terminal year last 12 month of life expenditures from both the 0-12 and 6-18 month analyses are found in Table 7. As mentioned before, these estimates were determined from the final models selected in each of the two analyses in each expenditure category and setting the number of months to 12. As mentioned earlier in Sections 6.1.1 and 6.1.2, sums of estimates of mutually exclusive and exhaustive measures within a larger category are not necessarily equal to the estimate in that larger category (e.g. the sum of the estimates from the 0-12 month analysis for the last year of life of $45,347 for Medicare and $24,078 for non-Medicare do not equal $66,125, the estimate for terminal year total expenditures; although the difference is small).

Table 7. Estimates (95% CI) of terminal year expenditures[a] for 0-12 and 6-18 month analyses with ratios of point estimates and their standard errors

	0-12 month	6-18 month	PE ratio[b]	SE ratio[c]	Efficiency ratio[d]
Total	66125 (63975, 68276)	67665 (64869, 70461)	1.023	1.300	1.018
By payer					
Medicare	45347 (43403, 47292)	44488 (42078, 46897)	0.981	1.239	0.971
Non-Medicare	24078 (22534, 25622)	23527 (22447, 24607)	0.977	0.699	0.548
Total private	14408 (13284, 15531)	13845 (13005, 14686)	0.961	0.748	0.586
Total public	52978 (50886, 55071)	53460 (50848, 56071)	1.009	1.248	0.978
Out-of-pocket	10531 (9516.9, 11546)	9944.6 (9184.4, 10705)	0.944	0.749	0.587
Medicaid	7920.1 (7229.5, 8610.7)	7863.1 (7169.4, 8556.8)	0.993	1.004	0.787
Private insurance	3779.1 (3187.1, 4371.1)	3857.4 (3460.4, 4254.3)	1.021	0.670	0.525
Total HMO	3024.1 (2526.2, 3522.1)	3347.4 (2803.7, 3891.2)	1.107	1.092	0.855
By service					
Dental	143.9 (101.0, 186.8)	181.2 (134.5, 227.8)	1.259	1.087	0.851
Facility	15097 (14051, 16142)	13860 (12893, 14826)	0.918	0.925	0.724
Home health	2048.1 (1595.6, 2500.7)	2168.6 (1879.8, 2457.4)	1.059	0.638	0.500
Hospice	4863.2 (4502.9, 5223.4)	4435.0 (3942.2, 4927.8)	0.912	1.368	1.072
Inpatient hospital	23030 (20888, 25173)	23727 (21948, 25506)	1.030	0.830	0.651
Institutional	6217.0 (5493.3, 6940.7)	6192.6 (5679.8, 6705.3)	0.996	0.709	0.555
Medical provider	9379.4 (8889.7, 9869.1)	10069 (9353.1, 10786)	1.074	1.463	1.146
Outpatient hospital	4062.7 (3411.6, 4713.9)	4121.0 (3629.1, 4613.0)	1.014	0.756	0.592
Prescribed medicine	2817.9 (2470.1, 3165.8)	2846.5 (2574.4, 3118.6)	1.010	0.782	0.613

a Values are given in 2013 dollars
b Ratio of point estimates from 6-18 month analysis to 0-12 month analysis
c Ratio of standard errors of point estimates from 6-18 month analysis to 0-12 month analysis. Note that these standard errors are not reported in the table
d Efficiency ratio = SE ratio × $\sqrt{n_{6-18}/n_{0-12}}$, where n is the sample size

In addition to these point estimates, Table 7 also contains the ratio of these point estimates, the ratio of the estimates of the standard error of these point estimates, and a sample-size adjusted ratio of the estimates of the standard errors (called the efficiency ratio), where the adjustment is the ratio of the square root of the sample sizes, that is $\sqrt{\frac{n_{6\text{-}18}}{n_{0\text{-}12}}}$. For these three ratios the 6-18 month estimate is the numerator and the 0-12 month estimate is the denominator. For example, the point estimate ratio of 1.023 for total expenses is the estimate $67,655 from the 6-18 month model divided by the estimate $66,125 from the 0 -12 model, indicating that the former estimate is 1.023 times as large as the later. Similarly, the SE ratio of 1.300 indicates that the standard error of the 6-18 month estimate is 1.300 times as large as that of the standard error for the 0 – 12 month estimate for last 12 month of life expenditures. Of note the standard errors themselves are not reported in the table to avoid making the table too busy. However, the sample size is smaller for the 6-18 month model than for the 0-12 month model. After multiplying 1.300 by the inverse of the square root of this ratio (as variances of point estimates are typically linear with respect to the inverse of the sample size) this corresponds to an efficiency of 1.018. The sample sizes are 2,626 for the 6-18 month analysis and 4,274 for the 0-12 analysis as reported in Table 1.

Graphs that overlay the regression equations from the 0-12 and 6-18 analyses are found in Figure 40 through Figure 57 in Section 12.1.3 starting on page 157. These graphs contain the regression curves with 95% confidence bands and the monthly means of expenditures (set at the mid-point of the month), with the curves and means from the 0-12 month analysis in blue and the curves and means from the 6-18 month analysis in red.

6.5.1 Comparison of estimates from 0-12 month and 6-18 months analyses to each other

Overall, the point estimates for terminal year expenditures from the 0-12 month analyses and the 6-18 month analyses in each of the expenditure categories were generally similar. Of the 18 categories, 11 of the point estimates from the 6-18 month analysis were within 5% of the point estimate of the 0-12 month analysis (6 were larger and 5 were smaller), 5 others were within 10% (2 larger, 3 smaller).

However, one 0-12 month analysis point estimate was almost 11% larger (total HMO), and one was almost 26% larger (dental). In the former case, this discrepancy may be largely explained by the effect of outliers in the 6-18 month analyses as can be seen from the monthly means for months 10 and 14, as can be seen in Figure 48 on page 161. In particular, for month 14, these beneficiaries would be a part of the 4-month mean point in the 0-12 month analysis, which is located almost on the regression line. From a qualitative standpoint, extrapolating the 0-12 month regression curve for total HMO expenditures out to 18 months would seem to fit most of the mean points beyond 12 months if we were to exclude the 14-month mean point. For the dental category, the expenditures in this category are very low in the last year of life, and so a moderate absolute discrepancy in these estimates translates to a large relative discrepancy. Tellingly, in both these categories the 95% confidence intervals at 12 months for both the 0-12 and 6-18 month models include the other estimate. Overall, we argue the point estimates from the two ranges considered seem to confirm each other.

Another way we can compare the results is by examining the overlap between the confidence intervals at 12-months. Looking at the results in this way, we found that in all but 3 categories the confidence interval for the 0-12 month analysis contained the 6-18 month point estimate and vice versa, this included the total and all of the by-payer categories. Of those 3 remaining categories, 2, hospice and medical provider expenditures, have 6-18 month confidence intervals that do contain the 0-12 month point estimate, while the 0-12 month confidence intervals do not contain the 6-18 month point estimate. For these two categories, we found that the 6-18 month analysis point estimates were 8.8% less for hospice and 7.4% more for medical provider expenditures when compared to the estimates from the 0-12 month analysis.

In the hospice category, there may be two issues that are driving this discrepancy. First, at 9 and 10 months from death (particularly the latter), the means for expenditures in these months are substantially lower in the 6-18 month versus those in the 0-12 month analysis. Moreover, the pattern of spending seen further out from death in the range from 13-18 months is lower than would be suggested by extrapolating out from the 0-12 month curve. This could be due to a considerable portion of hospice expenditures accruing in the last months of life, as indicated in the 0-12 month analysis, consistent with this category of spending being used for those who are known to be terminally ill. We could not think of any reason for the discrepancy in the medical provider expenditure terminal year estimates.

Neither the 0-12 month nor the 6-18 month confidence intervals for terminal year facility expenditures contain the point estimate from the other analysis. The discrepancy for this category was 8.2% lower for the 6-18 month point estimates versus the 0-12 month estimate. Again we were unsure of why we see a discrepancy between the estimates in this category.

Of note is that the two CIs at 12-months for all three of these expenditure categories (facility, hospice, and medical provider) still contain a sizable overlap, with the point estimates from the each analysis falling, at most, just outside the range of the CI of the other. As with the point estimate data, at least qualitatively, the results from these analyses seem to be mostly confirmatory of the other.

The ratio of the standard error of the 6-18 month terminal year estimate and that of the 0-12 month terminal year estimate was less than 1 for 10 of the 18 categories, 2 were between .8 and 1, 5 were between .7 and .8, and the remaining 3 were between .6 and .7. This ratio was greater than 1 for 8 categories, 3 were between 1 and 1.2, 3 were between 1.2 and 1.3, 1 was 1.368 (hospice), and 1 was 1.463 (medical provider). So overall, in spite of the reduced sample size of 2623 (61%) from losing subjects that did not have MCBS data in the 2 years prior to the calendar year of death the variance of the last year of life estimates from the 6-18 month data models was smaller than was those from 0-12 month models.

Since the sample sizes were not the same, 4,274 and 2,623 for the 0-12 and 6-18 month analyses, respectively, these ratios were adjusted based on the ratio of the square roots of the sample sizes, which we called the efficiency ratio. For these efficiency ratios, in all but 3 of the categories this ratio was less than 1, with 2 in the range .9 to 1, 2 in the range .8 to .9, 2 between .7 and .8, 2 between .6 and .7, and 7 between .5 and .6. These efficiency ratios indicate that on an equal playing field (i.e. the same number of observations in each model) using the 6-18 month analysis so that the terminal year estimate is in the middle of the range rather than at the edge, as in the 0-12 month analysis, would provide, in some cases substantially, lower variance estimates. Of the three categories with an efficiency ratio higher than 1, the total had an efficiency ratio of 1.018, hospice was 1.072, and medical provider was 1.146.

6.5.2 Comparison of our last 12 months of life expenditure estimates to those in the literature

Table 8, below, compares our last 12 months of life expenditure estimates with those from De Nardi et al in 2016, which used the 2008 MCBS, and French et al in 2018, which used the 2011 MCBS. Both studies expressed their estimates in 2014 dollars, we have adjusted these values to 2013 dollars. Included in this table are percentages giving the proportion of those costs to the total for each of the studies (again due to different models being fit across categories, sums of estimates of mutually exclusive and exhaustive measures within a larger category are not necessarily equal to the estimate in that larger category).

Terminal Medicare, Medicaid, and private insurance expenditure estimates were given as percentages in French (the others were given in dollar values), the values in the table were calculated from these percentages and the given total terminal expenditure estimate. Neither De Nardi et al (2016) nor French et al (2018) contained estimates for total private, total public, non-Medicare, total HMO, dental, or institutional costs, so these have been omitted from the table. Additionally, French et al (2018) did not contain estimates for the home health, hospice, medical provider, or prescribed medicine categories. Both papers combined certain categories together, with De Nardi et al (2016) combining home health and hospice expenditures together and French et al (2018) combining inpatient and outpatient hospital expenditures.

In a similar fashion, Table 9 compares the estimates from this paper with those from Hoover et al (2002) which used data from the 1992-1996 MCBS. Hoover et al did not include the total private or total public expenditure categories, so these have been omitted. This table gives both the 0-12 and 6-18 month terminal year expenditure point estimates, and their percentage of the total, and adds the original estimates from Hoover et al in 1996 dollars, and their percentage of the total, and also those same estimates CPI-adjusted to 2013 dollars. Ratios of the two sets of estimates from this paper to the equivalent categories from Hoover et al (2002) are also included.

Table 8. Estimates (% of total[a]) of terminal year expenditures[b] for this paper, De Nardi et al (2016) and French et al (2018)

	This paper			
	0-12 month	6-18 month	De Nardi[c]	French[d]
Total	66125 (100)	67665 (100)	58157 (100)	78815 (100)
By payer				
Medicare	45347 (69)	44488 (66)	41428 (71)	52018 (66)
Out-of-pocket	10531 (16)	9944.6 (15)	6396 (11)	9378 (12)
Medicaid	7920.1 (12)	7863.1 (12)	5806 (10)	7093 (9)
Private insurance	3779.1 (6)	3857.4 (6)	3129 (5)	6305 (8)
By service				
Facility	15097 (23)	13860 (20)	14751 (25)	13810 (18)
Home health	2048.1 (3)	2168.6 (3)	6072 (10)[f]	–
Hospice	4863.2 (7)	4435 (7)		–
Inpatient hospital	23030 (35)	23727 (35)	23617 (41)	34811 (44)[g]
Outpatient hospital	4062.7 (6)	4121 (6)	2824 (5)	
Medical provider	9379.4 (14)	10069 (15)	8364 (14)	–
Prescribed medicine	2817.9 (4)	2846.5 (4)	2519 (4)	–

a Note that mutually exclusive and exhaustive categories may not add to 100% due to model selection
b Values are given in 2013 dollars
d Estimates based on 2008 MCBS, original dollar values converted from 2014 to 2013 dollars
e Estimates based on 2011 MCBS, original dollar values converted from 2014 to 2013 dollars. Some values were given as percentages which were used to calculate dollar values in the table
f Home health and hospice were combined into one category
g Inpatient and outpatient hospital were combined into one category

Table 9. Estimates of terminal year expenditures (% of total[a]) for 0-12 month analysis, 6-18 month analysis, and Hoover et al (2002) (unadjusted and adjusted for inflation) with ratios of Hoover et al (2002) point estimates to 0-12 and 6-18 month analyses

	This paper (2013 dollars) [b]		Hoover et al (2002)		PE Ratio[c]	
	0-12 month	6-18 month	1996 dollars	2013 dollars[d]	0-12 months	6-18 months
Total	66125 (100)	67665 (100)	37581 (100)	55798	1.185	1.213
By payer						
Medicare	45347 (69)	44488 (66)	23739 (63)	35246	1.287	1.262
Non-Medicare	24078 (36)	23527 (35)	13842 (37)	20552	1.172	1.145
Out-of-pocket	10531 (16)	9944.6 (15)	5211 (14)	7737	1.361	1.285
Medicaid	7920.1 (12)	7863.1 (12)	5051 (13)	7499	1.056	1.048
Private insurance	3779.1 (6)	3857.4 (6)	2097 (6)	3114	1.214	1.239
Total HMO	3024.1 (5)	3347.4 (5)	641 (2)	952	3.177	3.517
By service						
Dental	143.9 (0.2)	181.2 (0.3)	93 (0.3)	138	1.042	1.312
Facility	15097 (23)	13860 (20)	8879 (24)	13183	1.145	1.051
Home health	2048.1 (3)	2168.6 (3)	1854 (5)	2753	0.744	0.788
Hospice	4863.2 (7)	4435 (7)	735 (2)	1091	4.456	4.064
Inpatient hospital	23030 (35)	23727 (35)	15461 (41)	22956	1.003	1.034
Institutional	6217 (9)	6192.6 (9)	2227 (6)	3307	1.880	1.873
Medical provider	9379.4 (14)	10069 (15)	6377 (17)	9468	0.991	1.063
Outpatient hospital	4062.7 (6)	4121 (6)	1846 (5)	2741	1.482	1.504
Prescribed medicine	2817.9 (4)	2846.5 (4)	653 (2)	970	2.906	2.936

a Note that mutually exclusive and exhaustive categories may not add to 100% due to model selection
b Values are given in 2013 dollars
c Ratio of point estimates from 0-12 month analysis and 6-18 month analysis to inflation adjusted Hoover et al (2002) estimates
d Percentages omitted because they are the same as the previous column

Total spending in the last year of life was estimated at \$66,125 (95% CI: 63,975-68,276) and \$67,665 (95% CI: 64,869-70,461) based on the 0-12 month and 6-18 month analyses, respectively (both in 2013 dollars). These estimates fall in the middle of two recent estimates for total terminal year medical expenditures from De Nardi et al (2016) and French et al (2018), of \$58,157 based on the 2008 MCBS data and \$78,815 based on the 2011 MCBS data, respectively (originally given as \$59,100 and \$80,094, respectively in 2014 dollars). Some of the discrepancy may be due to the smaller sample sizes used in the De Nardi and French studies, as they only focused on a single year of MCBS data. Also both of these studies relied on the Hoover et al (2002) approach (which was also the basis for the models used in this study) of fitting the model $Y = \beta_0 + \beta_1\sqrt{m} + \beta_2 m + \beta_3 m^2$. However, in both studies, there was no indication that any selection process of the model terms was applied as was used by Hoover et al (2002) and if that was not used potential overfitting could have impacted the 12-month estimates from those papers.

However, the estimates for total terminal year expenditures here were higher than those of Hoover et al (2002) who did apply selection to the terms. But the data in that paper was from about 15 years earlier and adjustment of that result from 1996 to 2013 dollars would not account for chronological changes in medical expenditures that differed from those in the CPI. The estimate for total terminal year medical expenditures for 1992-1996 was \$37,581 in 1996 dollars (Hoover et al. 2002). Applying a CPI adjustment shows this is approximately \$55,798 in 2013 dollars. The estimates from this study are 18.5% (0-12 month model) and 21.3% (6-18 month model) higher than this adjusted estimate.

Terminal year Medicare expenditures were the main driver of total terminal year medical expenditures here being 69% and 66% of the total for the 0-12 and 6-18 month analyses, respectively. These were similar to those percentages as reported by De Nardi et al (2016), French et al (2018), and Hoover et al (2002), of 71%, 66%, and 63%, respectively. Compared with studies that focused solely on Medicare expenditures, the values in this paper of $45,347 (95% CI: 43,403, 47,292) and $44,488 (95% CI: 42,078, 46,897) for the 0-12 and 6-18 month analyses here were higher than those from Shugarman et al (2004) (covering a random sample of Medicare beneficiaries from 1996-1999) of approximately $34,400 (given as 24.6 in thousands of 1999 dollars, converted here to 2013 dollars), similar to Lubitz and Riley (2010) (covering Medicare beneficiaries in 2006) of $45,037 ($38,975 in 2006 dollars, converted here to 2013 dollars), and lower than Davis et al (2016) (covering Medicare beneficiaries in 2012) of $50,757 ($50,024 in 2012 dollars, converted here to 2013 dollars). These estimates, along with those from Hoover et al (2002), De Nardi et al (2016), and French et al (2018), can be seen in descending order, after inflation-adjustment to 2013 dollars, below in Table 10. Calendar trends may account for some of the differences seen in these estimates as the two lowest values are based on analyses done in the 1990s.

Table 10. Estimates of terminal year Medicare expenditures from the literature in descending order

Paper	Years covered	Medicare expenditure estimate[a]
French et al (2018)	2011	52018
Davis et al (2016)	2012	50757
Here 0-12 month analysis	**2006-2013**	**45347**
Lubitz and Riley (2010)	2006	45037
Here 6-18 month analysis	**2006-2013**	**44488**
De Nardi et al (2016)	2008	41428
Hoover et al (2002)	1992-1996	35246
Shugarman et al (2004)	1996-1999	34400

a Values from all papers converted to 2013 dollars using CPI index

The two largest remaining payer expenditure categories were out-of-pocket and Medicaid expenditures, similar to results found in Hoover et al (2002) and De Nardi et al (2016). Out-of-pocket spending was 15.9% and 14.7% of the total, respectively, based on the 0-12 and 6-18 month analysis, slightly higher than the 13.8% reported in Hoover et al (2002) and higher than the 11% reported by De Nardi et al (2016). Medicaid expenditures made up 12.0% and 11.6% of total spending, slightly lower than the 13.4% reported by Hoover et al (2002), but slightly higher than the 10% reported in De Nardi et al (2016).

The three highest service expenditure categories were inpatient hospital services, long-term facilities, and medical providers, again consistent with Hoover et al (2002) and De Nardi et al (2016). Inpatient hospital costs were 34.8% and 35.1% of the total for the 0-12 and 6-18 month analyses, respectively, as compared to 41% from both Hoover et al (2002) and De Nardi et al (2016). Facility costs were 22.8% and 20.5% of the total, respectively, versus 23.6% from Hoover et al (2002) and 25% from De Nardi et al (2016). Finally, medical provider costs were 14.2% and 14.9% of the total, respectively; Hoover et al. (2002) found it was higher at 17% of the total, but the results from De Nardi et al (2016) were similar at 14.4%.

When compared with Hoover et al (2002) from 15 years earlier in the MCBS, the estimates for almost all comparable expenditure categories were consistently higher in this study even after adjustment to 2013 dollars to account for inflation. Of note were considerably higher terminal year expenditure estimates for HMO spending, for hospice services, and for prescription drugs, with 0-12 and 6-18 month estimates being 318% and 351% for HMO spending, 446% and 406% for hospice services, and 291% and 294% for prescription drugs of the estimates from Hoover et al (2002). Home health services expenditure estimates decreased from 1992-1996, with the estimates from the 0-12 and 6-18 month analyses being only 74.4% and 78.8% of the inflation-adjusted estimates from Hoover et al (2002).

7 SENSITIVITY ANALYSES

7.1 Sensitivity analysis comparing given date of death versus midpoint of death month using 1992-1994 MCBS data

In initial analyses of the MCBS data, it was discovered that starting in 1995 and continuing through 2013, the dates of death given in the data sets were recoded to be at the end of the month of death rather than the actual date of death. If we had mistakenly used the death dates given in the MCBS, our models would have been incorrectly specified. In particular, our curves would have been shifted to the right, resulting in intercept estimates that were too low. In some cases, this may have resulted intercepts remaining in the 0-12 month model, while with the correct dates of death, they would not have been included in the final model. While it was possible for us to purchase the majority of true death dates, the expense of obtaining these data was cost prohibitive.

Death rates in the US vary over the year, with higher death rates in the winter months and lower death rates in the summer months (Xu 2019). However, since the month of death was known, we recoded each decedent beneficiary's date of death to the middle of the month of death. This was consistent with what we felt was a reasonable assumption, as others have shown (Law and Brookmeyer 1992), that given an interval for an event to happen, a uniform distribution (or midpoint) approximation is reasonable.

To justify this use of the midpoint of the month as the date of death, a sensitivity analysis was done by performing the 0-12 month analysis described in Section 6.1.1 (page 36) twice on the 1992-1994 MCBS data (where actual death dates were available), first using the midpoint of the death month and then using the given death dates. These years were used because actual death dates were given for the vast majority of respondents. A handful of patients may have had death dates set to the end of the month because the actual day of death was unknown, these dates were used as given for the analysis using the given death dates. As before, mean expenditures were modeled with linear polynomial models using BRR with a Fay's coefficient of 0.3 starting with 4 terms: $Y = \beta_0 + \beta_1\sqrt{m} + \beta_2\sqrt{\min{(m,6)}} + \beta_3 m$, where Y is the expense of interest and m is the number of months of follow-up. For the first set of models, using the given date of death, m was based on the number of days alive in the calendar year of death using the given date of death expressed in months. For the second set of models, using the midpoint of the month of death, m was based on the number of days alive in the calendar year of death using the midpoint of the month of death expressed in months.

For both sets of models, least significant terms were removed by backward selection until all terms were significant at $p < 0.05$. If, however, both the $\sqrt{m}$ and $\sqrt{\min{(m,6)}}$ terms were in the final model, the backward selection was re-run after first eliminating the least significant of these two terms. Removal of terms stopped when a model was reduced to the point of having only one non-intercept term. To estimate average terminal year expenditures, point estimates and confidence intervals were calculated from the coefficient estimates and their covariances by setting $m = 12$. Unfortunately, the 6-18 month analysis (see Section 6.1.2 on page 38) could not be replicated as the 2-year longitudinal sample and BRR replicate weights as used in this analysis were not available prior to 2006. Additionally, respondents from 1992 did not have prior year data as this was the first year where MCBS Cost and Use data were available.

7.1.1 Demographics of this sensitivity analysis data set

The demographics on sex, race, age category, and US Census region for the samples of decedent beneficiaries used in the 1992-1994 MCBS are noted below in Table 11. Relative to the demographics of the decedent beneficiaries in the 0-12 and 6-18 month analyses described in Section 6.2 in Table 1 (page 44), the breakdowns by sex and US Census regions are similar. For the age categories, the 1992-1994 decedents tend to be younger, with a lower percentage classified as 85+ relative to both data sets taken from the 2006-2013 MCBS and higher percentages in the other four younger categories representing those from 65 to 84. This is likely due to increasing age at death in the ensuing years, but we do not anticipate this to have a major effect on the validity of this analysis as a check on the analyses using the 2006-2013 MCBS data. Finally, while the White, Black, and Other racial categories correspond well between the 2006-2013 data sets and the 1992-1994 data, the Hispanic and Asian categories were smaller, and the North American Native category was not counted in the latter. However, given the small sizes of these racial categories, it is unlikely that differences here would greatly influence overall results. It is possible that the larger proportion of records in the Unknown racial category in the 1992-1994 data might capture some of these discrepancies. As was done for the 0-12 month and 6-18 month analyses based on the 2006-2013 MCBS data, sample weighted means and standard deviations of last calendar year of life medical expenditures for decedents in each expenditure category, as well as the average duration of backwards follow-up from death (i.e. number of months lived during last calendar year of life) are given in Table 12.

Table 11. Demographics for decedent beneficiaries in the 1992-1994 MCBS

Total decedent beneficiary records, n	1943
Sex, n (%)	
Female	1099 (56.6)
Male	844 (43.4)
Race, n (%)	
White	1684 (86.7)
Black	179 (9.2)
Hispanic	5 (0.3)
Asian	2 (0.1)
Other	20 (1.0)
Unknown	53 (2.7)
Age category, n (%)	
65-69	164 (8.4)
70-74	185 (9.5)
75-79	303 (15.6)
80-84	456 (23.5)
85+	835 (43.0)
US Census region, n (%)	
Midwest	456 (23.5)
Northeast	395 (20.3)
Puerto Rico	23 (1.2)
South	720 (37.1)
West	349 (18.0)
Calendar year, n (%)	
1992	620 (31.9)
1993	651 (33.5)
1994	672 (34.6)

Table 12. Mean (SEM)[a] for death backwards follow-up duration and unadjusted expenditures by category	
Duration of follow-up, months	5.83 (0.09)
Expenditures[b,c]	
Total	33416 (1001.4)
By payer	
Medicare	22704 (884.3)
Non-Medicare	10712 (322.6)
Total private	6614 (271.8)
Total public	26638 (910.7)
Out-of-pocket	4415 (234.1)
Medicaid	3426 (192.8)
Private insurance	2199 (161.7)
Total HMO	469.4 (124.3)
By service	
Dental	58.08 (17.69)
Facility	5896 (297.5)
Home health	1382 (111.8)
Hospice	611.8 (75.06)
Inpatient hospital	16658 (741.2)
Institutional	1461 (113.3)
Medical provider	5655 (249.0)
Outpatient hospital	1258 (97.01)
Prescribed medicine	436.2 (22.02)

a SEMs estimated using BRR with Fay's method
b Values are given in 2013 dollars

7.1.2 Results

For each of the eighteen categories of expenditures the parameter estimates and their 95% confidence intervals for the final selected models using both the given date of death and the midpoint of the month of death for each category of expenditure can be found in Table 13, below. Terminal year estimates and their 95% confidence intervals for the selected models for both the given date of death and the midpoint of the month of death, along with the ratio between the given date of death estimate and the midpoint of death estimate (e.g. for total expenditures the ratio of 0.993 is calculated by dividing

$54,480 from the model that used the given date of death, by $54,861, from the model that used the midpoint of the month of death) are found in Table 14.

Figure 58 to Figure 77 in Section 12.2.1 starting on page 166 show the superimposed curves with 95% confidence bands for each of the two models, with the curve for the model using the given date of death in blue and the curve for the model using the midpoint of the month of death in red. Means of expenditures for the last calendar year of life by month of death (set at the mid-point of the month) are shared between the two curves so these points are in black. These figures are organized such that the total expenditure category is first, followed by expenditure categories based on the payer of services, followed by those categories based on the type of service involved in the expenditure, as in Table 13 and Table 14, below.

Table 13. Parameter estimates (95% CI) for model terms in 0-12 month analysis of given date of death vs midpoint of month of death from 1992-1994

	Using given date of death				Using midpoint of month			
	Intercept	Months	$\sqrt{\text{Months}}$	$\sqrt{\text{min(Months,6)}}$	Intercept	Months	$\sqrt{\text{Months}}$	$\sqrt{\text{min(Months,6)}}$
Total	13612 (10945, 16278)	3405.6 (2888.8, 3922.5)	–	–	13540 (10849, 16232)	3443.3 (2920.3, 3966.3)	–	–
By payer								
Medicare	11177 (8701.3, 13652)	1982.4 (1505.3, 2459.4)	–	–	11109 (8590.4, 13627)	2008.8 (1524.3, 2493,4)	–	–
Non-Medicare	–	1154.3 (824.4, 1484.2)	–	1991.0 (1085.0, 2897.1)	–	1158.1 (821.0, 1495.2)	–	2012.1 (1086.0, 2938.3)
Total private	–	462.8 (187.6, 737.9)	–	1969.9 (1182.7, 2757.1)	–	456.0 (177.4, 734.5)	–	2008.3 (1211.3, 2805.3)
Total public	11251 (8766.5, 13735)	2646.2 (2176.4, 3116.0)	–	–	11172 (8651.1, 13694)	2679.5 (2201.5, 3157.4)	–	–
Out-of-pocket	–	405.4 (186.9, 623.8)	–	1034.2 (442.2, 1626.3)	–	400.6 (180.6, 620.7)	–	1061.2 (469.6, 1652.7)
Medicaid	–	593.9 (516.4, 671.4)	–	–	–	598.5 (520.0, 677.1)	–	–
Private insurance	–	–	–	1115.5 (954.3, 1276.6)	–	–	–	1119.5 (959.2, 1279.9)
All HMO	–	–	198.9 (105.4, 292.3)	–	–	–	197.9 (105.8, 290.0)	–
By service								
Dental	–	11.0 (3.45, 18.5)	–	–	–	11.2 (3.35, 19.0)	–	–
Facility	–	1007.4 (887.6, 1127.3)	–	–	–	1012.2 (891.8, 1132.6)	–	–
Home health	–	233.6 (191.8, 275.4)	–	–	–	236.1 (194.0, 278.3)	–	–
Hospice	–	–	–	309.4 (230.0, 388.8)	–	–	–	309.8 (230.5, 389.0)
Inpatient hospital	10503 (8082.0, 12924)	1058.4 (647.3, 1469.5)	–	–	10405 (7961.3, 12848)	1083.3 (666.4, 1500.2)	–	–
Institutional	–	233.3 (193.2, 273.3)	–	–	–	126.0 (4.12, 247.8)	–	373.4 (20.9, 726.0)
Medical provider	–	350.4 (139.8, 560.9)	–	1834.1 (1187.5, 2480.6)	–	369.8 (158.0, 581.7)	–	1786.0 (1139.2, 2432.7)
Outpatient hospital	–	210.1 (172.0, 248.1)	–	–	–	211.6 (173.6, 249.6)	–	–
Prescribed medicine	–	73.9 (65.5, 82.3)	–	–	–	74.5 (65.9, 83.0)	–	–

Cells without an estimate indicate that parameter was not selected in the final model.

Table 14. Estimates (95% CI) of terminal year expenditures[a] in 0-12 month analysis of given date of death versus midpoint of month of death from 1992-1994

	Using given date of death	Using midpoint of month	Point estimate ratio[b]
Total	54480 (50030, 58929)	54861 (50361, 59361)	0.993
By payer			
Medicare	34965 (30904, 39026)	35215 (31107, 39323)	0.993
Non-Medicare	18728 (16741, 20716)	18826 (16801, 20850)	0.995
Total private	10378 (8777.3, 11980)	10391 (877.4, 12010)	0.999
Total public	43005 (38972, 47038)	43326 (39237, 47415)	0.993
Out-of-pocket	7397.7 (6024.8, 8770.6)	7407.0 (6015.2, 8798.9)	0.999
Medicaid	7127.1 (6197.1, 8057.1)	7182.5 (6240.3, 8124.8)	0.992
Private insurance	2732.3 (2337.7, 3127.0)	2742.3 (2349.7, 3135.0)	0.996
All HMO	688.9 (365.2, 1012.6)	685.5 (366.5, 1004.6)	1.005
By service			
Dental	131.5 (41.3, 221.6)	134.3 (40.2, 228.4)	0.979
Facility	12089 (10651, 13527)	12146 (10702, 13591)	0.995
Home health	2803.7 (2301.7, 3305.7)	2833.4 (2327.6, 3339.3)	0.990
Hospice	757.9 (563.4, 952.4)	758.8 (564.7, 952.9)	0.999
Inpatient hospital	23204 (19925, 26484)	23405 (20083, 26726)	0.991
Institutional	2799.5 (2318.8, 3280.2)	2426.3 (1732.2, 3120.4)	1.154
Medical provider	8697.0 (7478.4, 9915.6)	8812.8 (7577.6, 10048)	0.987
Outpatient hospital	2520.8 (2064.1, 2977.5)	2539.1 (2082.7, 2995.5)	0.993
Prescribed medicine	887.1 (786.5, 987.7)	893.6 (790.9, 996.4)	0.993

a Values are given in 2013 dollars

b Ratio of point estimates from given date of death model and midpoint of month model

7.1.3 Conclusions

For every expenditure category, except for the institutional expenditure category, the same model terms were selected regardless of the way the date of death was calculated. The parameter estimates and 12-month estimates for both the given date of death and midpoint of month of death analyses for all of these expenditure category are extremely close as seen in Table 13 and Table 14.

For the institutional expenditure category, while the 12-month estimates are within each models 95% CI (though this category did have the largest difference in point estimates), the models selected were not the same, with the given date of death model including only the linear in months term, while the midpoint of month model had both the linear in months term and the $\sqrt{\min(m,6)}$ terms in the model. In the given date of death model, the $\sqrt{\min(m,6)}$ term was removed last with a p-value of 0.0587, while the p-value for this term in the midpoint of month model was 0.0381. This probably underscores that just like baseball, the selection process can be a game of inches (i.e. between a homerun and a fly ball). Due to the nature of the Type I and Type II errors in this setting, we make no conclusions on which of the two curves is better. In addition to Figure 72 which shows the superimposed curves of each of the two selected models, Figure 73 superimposes the curves for both date of death methods using the given date of death model, while Figure 74 does the same using the midpoint date of death model.

For the private insurance and hospice expenditure categories, the final model selected solely included the $\sqrt{\min(m,6)}$ term, which resulted in a model that indicated no additional expenditures in months 6-12. For private insurance, this model does not make much sense. The issue here may be one of sample size and many 0 values for private insurance expenditures, with nearly half of all decedents having no private insurance expenditures in the last calendar year of life (data not shown). While this also holds true in the 0-12 month analysis using the 2006-2013 MCBS (data not shown), the nearly four-fold increase in sample size may mitigate the effect of the 0 values. Additionally, there may be issues of outlier effects as there is a decline in mean calendar year expenditures from August to November as shown in Figure 65.

On the other hand, since hospice services are used close to death, selection of this model could make some sense as decedents with 7-12 months of MCBS data may only use these services in the last 6 months of life. Another issue here is that nearly 91% of decedent beneficiaries had no hospice expenditures in the last calendar year of life (data not shown). This is different from the 2006-2013 data where only 58% of decedents had no hospice expenditures in the last calendar year of life (data not shown).

The curves for both HMO and dental expenditures had very wide confidence bands. This is likely due to high numbers of decedents with no expenditures in these categories in the last calendar year of life, with 94% of decedents having no HMO expenditures and 91% of decedents having no dental expenditures in the last calendar year of life between 1992 and 1994. In the 2006-2013 MCBS most decedents also reported no expenditures in these categories with 81% having no HMO expenditures and 92% having no dental expenditures, but again the larger sample sizes for these models may have dampened down the width of the confidence intervals for this curve.

7.2 Sensitivity analysis of linear term versus square root term in the 6-18 month analysis

In constructing the 6-18 month analysis, described in Section 6.1.2 (page 38), our primary motivation was to use data so that our estimate for terminal year expenditures fell into the middle, rather than the edge, of the data range as in the 0-12 month analysis (Section 6.1.1). We also knew that for many categories of medical expenditures prior literature had found that many of the terminal year costs were realized in the months immediately preceding death (i.e. within 6 months of death) (Hoover et al 2002, Davis et al 2016), which was the justification for the inclusion of the two square root terms in our models ($\sqrt{m}$ and $\sqrt{\min(m,6)}$). We had expected that by using the 6-18 month range instead of the 0-12 range, more linear in months models would have been selected by the data. As seen in Table 5, we found instead that half (9 out of 18) of the models selected contained the square root in months term without the inclusion of the linear in months term. In order to explore how much of a difference fitting a linear model would have on the estimates of terminal year expenditures in those categories, we fit the linear polynomial model $Y = \beta_0 + \beta_1 m$ instead of the originally selected model of $Y = \beta_0 + \beta_1\sqrt{m}$ in these expenditure categories. In these models, Y is the expense of interest and m is the number of months of follow-up based on the number of days alive in the calendar year of death and the year prior for those who died in June or earlier of the calendar year of death using the midpoint of the month. As with the original analysis, the BRR method with a Fay's coefficient of 0.3 was used for variance estimation.

7.2.1 Results

Of the 9 categories with the square root in months term as the sole non-intercept term in the final selected model, five of these categories were by-payer categories: non-Medicare, total private, out-of-pocket, Medicaid, and total HMO expenditures. The remaining four were the by-service categories of dental, facility, home health, and hospice expenditures. Parameter estimates for the original square root term model and the newly fit linear term model in these 7 expenditure categories can be found in Table 15. The equivalent 12-month estimates for both model fits are found in Table 16, along with ratios of the point estimate and standard error from the linear model to the equivalent point estimate and standard error from the original square root model.

Figure 78 to Figure 86 in Section 12.2.2 starting on page 177 show the superimposed curves with 95% confidence bands for each of the two models, with the curve for the model for the original model using the square root term in blue and the curve for the new model using the linear term instead in red. Monthly means of expenditures (set at the mid-point of the month) are shared between the two curves, so these points are in black. These figures are organized in the same order as in Table 15 and Table 16, below.

Table 15. Parameter estimates (95% CI) for model terms in 6-18 month analysis, linear term versus square root term models

	Using linear term		Using square root term	
	Intercept	Months	Intercept	$\sqrt{\text{Months}}$
By payer				
Non-Medicare	6622.1 (2857.2, 10387)	1379.6 (1043.3, 1715.9)	-8864.5 (-16042, -1687.0)	9350.6 (7157.5, 11544)
Total private	4588.5 (1881.4, 7365.6)	755.4 (505.2, 1005.7)	-3955.4 (-9339.1, 1428.3)	5138.7 (3487.6, 6789.7)
Out-of-pocket	2808.7 (749.4, 4867.9)	582.3 (387.2, 777.3)	-3836.2 (-7909.7, 237.4)	3978.2 (2691.2, 5265.2)
Medicaid	1279.5 (-866.4, 3425.5)	537.3 (333.2, 741.4)	-4719.1 (-8937.7, -500.4)	3632.1 (2299.4, 4964.9)
Total HMO	1912.5 (477.3, 3347.7)	117.1 (-2.67, 236.8)	523.1 (-2151.2, 3197.4)	815.3 (17.9, 1612.8)
By service				
Dental	-51.0 (-148.9, 46.9)	18.9 (10.3, 27.6)	-269.5 (-452.0, -87.0)	130.1 (72.7, 187.5)
Facility	3744.0 (649.4, 6838.7)	825.5 (528.9, 1122.1)	-5574.2 (-11716, 567.9)	5610.1 (3668.0, 7552.2)
Home health	374.5 (-284.5, 1033.6)	146.4 (88.7, 204.1)	-1264.4 (-2515.9, -13.0)	991.0 (602.8, 1379.3)
Hospice	2298.9 (974.0, 3623.7)	174.3 (51.0, 297.6)	299.3 (-2358.0, 2956.5)	1193.9 (362.3, 2025.5)

Table 16. Estimates (95% CI) of terminal year expenditures[a] in 6-18 month analysis, linear term versus square root term models

	Using linear term	Using square root term	PE ratio[b]	SE ratio[c]
By payer				
Non-Medicare	23177 (22133, 24222)	23527 (22447, 24607)	0.985	0.967
Total private	13653 (12839, 14468)	13845 (13005, 14686)	0.986	0.968
Out-of-pocket	9796.1 (9062.6, 10530)	9944.6 (9184.4, 10705)	0.985	0.965
Medicaid	7727.2 (7064.1, 8390.2)	7863.1 (7169.4, 8556.8)	0.983	0.956
Total HMO	3317.1 (2780.1, 3854.2)	3347.4 (2803.7, 3891.2)	0.991	0.988
By service				
Dental	176.3 (130.6, 222.0)	181.2 (134.5, 227.8)	0.973	0.980
Facility	13650 (12729, 14571)	13860 (12893, 14826)	0.985	0.952
Home health	2131.5 (1848.6, 2414.4)	2168.6 (1879.8, 2457.4)	0.983	0.980
Hospice	4390.5 (3913.2, 4867.7)	4435.0 (3942.2, 4927.8)	0.990	0.968

a Values are given in 2013 dollars
b Ratio of point estimate from the linear term model to point estimate from the square root term model
c Ratio of standard error of the point estimate from the linear term model to the standard error of the point estimate from the square root term model

7.2.2 Conclusions

Due to the concavity of a square root function, when comparing the square root models with the linear models for the same expenditure category, the terminal year estimates are slightly larger for the square root models (since the estimate is in the middle of the range). However, in all cases, there are not any appreciable differences in these estimates, as seen in the second to last column of Table 16, with the largest difference being under 3% (dental expenditures). Additionally, while the variances are slightly higher for the 12-month estimates coming from the square root models, the differences are small and can likely be attributed to the difference in the location of $m = 12$ relative to the range of the data. Namely, when using a linear model, 12 months is located in the exact center of the range of 6 to 18 months, where variance is minimized, however, $\sqrt{12}$ is not quite in the center of the range (slightly on the lower end) of the range $\sqrt{6}$ to $\sqrt{18}$.

For non-Medicare, total private, out-of-pocket, Medicaid, facility, and home health expenditures, the intercept changed from negative to positive when switching from the square root to the linear model. Because the model is fit for data running from 6 months to 18 months this is not an issue as it cannot predict the costs outside of this range well (i.e. the intercept is for 0 months prior to death). However, qualitatively, since negative intercepts for the square root models in the 6-18 month analysis signify that the acceleration of expenditures on the square root scale in the 6-18 month analysis slows down on that scale when moving beyond the range to closer than 6 months before death, it is not surprising that all the 0-12 month models for these categories contain a linear term (some also have one of the square root terms), which does indicate some attenuation of the acceleration in expenditures closer to death.

7.3 Sensitivity analysis on inclusion of the intercept in the 6-18 month analysis

As mentioned in the sensitivity analysis above, our major motivation behind the 6-18 month analysis was to develop a set of data where the 12-month terminal expenditure estimates were located in the middle of the data range rather than at the edge. We had also hypothesized that in the 6-18 month analysis, we would see more of the models be strictly linear in months as compared to the 0-12 month analyses, because we believed that there would not be a substantive increase in rate of expenditures going from 18 down to 6 months but that there would often be in the final 6 months of life, as more "heroic" life-saving procedures would cumulatively be implemented in this final stage.

Accordingly, to account for any spending pattern differences in the last 6 months of life, unlike the other terms in the 6-18 month analysis and unlike the 0-12 month analysis, we decided to not employ the backwards selection process on the intercept, leaving it in all final models, regardless of its significance. As seen in Table 5, we found that in 7 out of 18 of the models selected the intercept term would have been removed via backwards selection at the 0.05 significance level. In order to explore how much of a difference applying the backwards selection process on the intercept would have on the estimates of terminal year expenditures in those categories, the backward selection was rerun on these 7 categories allowing the removal of the intercept. Ultimately, in all these 7 cases, the model selected had the same terms as the original backwards selection process with just the intercept removed. Since the categories that had a non-significant intercept contained either the linear in months term or the square root in months term, and not both, in the final model, for each of these categories either the linear polynomial model $Y = \beta_1 m$ or the model $Y = \beta_1 \sqrt{m}$ was fit depending on whether the original final model contained the linear or square root term, respectively. As before, Y is the expense of interest and m is the number of months of follow-up based on the number of days alive in the calendar year of death and the year prior for those who died in June or earlier of the calendar year of death using the midpoint of the month. As with the original analysis, the BRR method with a Fay's coefficient of 0.3 was used for variance estimation.

7.3.1 Results

Of the 7 categories with non-significant intercept terms in final selected model, three of these categories were the by-payer categories of total private, out-of-pocket, and total HMO expenditures. The remaining four were the by-service categories of facility, hospice, medical provider, and outpatient hospital expenditures. Parameter estimates for the original model including the intercept and the model fit without the intercept in these 7 expenditure categories can be found in Table 17. The equivalent 12-month estimates for both model fits are found in Table 18.

Figure 87 to Figure 93 in Section 12.2.3 starting on page 182 show the curves with 95% confidence bands for each of the two models, with the curve for the original model with an intercept in blue and the curve for the new model without the intercept in red. Monthly means of expenditures (set at the mid-point of the month) are shared between the two curves, so these points are in black. These figures are organized in the same order as in Table 17 and Table 18, below.

Table 17. Parameter estimates (95% CI) for model terms in 6-18 month analysis, model without intercept versus model with intercept

	Without intercept		With intercept		
	Months	$\sqrt{\text{Months}}$	Intercept	Months	$\sqrt{\text{Months}}$
By payer					
Total private	–	4011.7 (3761.1, 4262.3)	-3955.4 (-9339.1, 1428.3)	–	5138.7 (3487.6, 6789.7)
Out-of-pocket	–	2885.2 (2658.8, 3111.6)	-3836.2 (-7909.7, 237.4)	–	3978.2 (2691.2, 5265.2)
Total HMO	–	964.4 (806.4, 1122.3)	523.1 (-2151.2, 3197.4)	–	815.3 (17.9, 1612.8)
By service					
Facility	–	4021.9 (3729.9, 4314.0)	-5574.2 (-11716.2, 567.9)	–	5610.1 (3668.0, 7552.2)
Hospice	–	1279.1 (1132.7, 1425.6)	299.3 (-2358.0, 2956.5)	–	1193.9 (362.3, 2025.5)
Medical provider	836.8 (768.5, 905.1)	–	359.1 (-2064.2, 2782.4)	809.2 (574.2, 1044.2)	–
Outpatient hospital	343.9 (299.0, 388.8)	–	-71.0 (-1522.8, 1380.7)	349.3 (209.9, 488.7)	–

Table 18. Estimates (95% CI) of terminal year expenditures[a] in 6-18 month analysis, model without intercept versus model with intercept

	No intercept model	Intercept model	PE ratio[b]	SE ratio[c]
By payer				
Total private	13987 (13029, 14765)	13845 (13005, 14686)	1.004	1.033
Out-of-pocket	9994.6 (9210.3, 10779)	9944.6 (9184.4, 10705)	1.005	1.032
Total HMO	3340.6 (2793.6, 3887.7)	3347.4 (2803.7, 3891.2)	0.998	1.006
By service				
Facility	13932 (12921, 14944)	13860 (12893, 14826)	1.005	1.047
Hospice	4431.1 (3923.8, 4938.4)	4435.0 (3942.2, 4927.8)	0.999	1.029
Medical provider	10041 (9221.5, 10861)	10069 (9353.1, 10786)	0.997	1.144
Outpatient hospital	4126.6 (3587.9, 4665.4)	4121.0 (3629.1, 4613.0)	1.001	1.095

a Values are given in 2013 dollars
b Ratio of point estimates from model without intercept and model with intercept
c Ratio of standard errors of point estimates from model without intercept and model with intercept

7.3.2 Conclusions

In each of the 7 categories analyzed in this sensitivity analysis, the terminal year point estimates are quite similar, never differing by more than 0.5% (out-of-pocket), as can be seen from the second-to-last column of Table 18. As can be expected, those models with negative intercepts in the original analysis had slightly higher estimates at 12-months when compared to the model without an intercept, while those with positive intercepts in the original analysis had slightly lower 12-month estimates in the model without an intercept.

8 COMPARISON OF TSE AND BRR FOR VARIANCE ESTIMATION IN ESTIMATING TERMINAL YEAR MEDICAL EXPENDITURES USING THE MCBS

As mentioned earlier, previous studies to measure terminal year medical expenditures using the MCBS either used the TSE method for variance estimation (Hoover et al 2002) or did not report variances (De Nardi et al 2016, French et al 2018). Currently CMS advocates using Fay's BRR method with a Fay's perturbation factor of 0.3 rather than the TSE method for variance estimation. Therefore, this paper followed that guidance for these analyses.

However, since comparisons between these approaches have never been made using the MCBS data and little exists in the statistical literature to compare these two methods, we decided to assess the differences in using the BRR method instead of the TSE method. Consequently, the final models for all classes of medical expenditures determined in the 0-12 and 6-18 month analyses were redone using the TSE method to calculate variances. For each of the parameter estimates for these models and for the 12-month terminal year expenditure estimates the standard errors were computed and the ratio of those obtained using the BRR method over those from the TSE method were calculated.

8.1 Results

Note that since these methods are solely used for variance estimation the point estimates for parameters and terminal year medical expenditures used in both methods are the same. Accordingly, this section focuses on the standard errors of these estimates.

8.1.1 Based on the 0-12 month analysis

BRR and TSE standard errors for the parameter estimates in the 0-12 month analyses of medical expenditures are presented in Table 19. The ratios between the BRR and TSE standard error estimates for the parameters in these models are found in Table 20. Standard errors using both methods of variance estimation and the ratio of BRR standard error to TSE standard error for the 12-month estimate of terminal medical expenditures for all analyzed categories using the 0-12 month data are given in Table 21.

Table 19. Standard error estimates for model terms in 0-12 month analysis, TSE method and BRR method

	TSE				BRR			
	Intercept	Months	$\sqrt{\text{Months}}$	$\sqrt{\min(\text{Months},6)}$	Intercept	Months	$\sqrt{\text{Months}}$	$\sqrt{\min(\text{Months},6)}$
Total	–	–	369.2	–	–	–	312.9	–
By payer								
Medicare	–	–	319.8	–	–	–	283.0	–
Non-Medicare	–	127.8	–	354.8	–	123.9	–	347.6
Total private	–	137.1	–	353.2	–	126.0	–	322.5
Total public	–	–	332.5	–	–	–	304.5	–
Out-of-pocket	–	109.7	272.7	–	–	109.0	257.9	–
Medicaid	–	33.16	–	–	–	29.01	–	–
Private insurance	–	57.27	–	172.2	–	51.76	–	158.8
All HMO	–	–	77.21	–	–	–	72.46	–
By service								
Dental	–	1.77	–	–	–	1.80	–	–
Facility	–	41.49	–	–	–	43.92	–	–
Home health	–	39.89	–	110.0	–	37.52	–	99.99
Hospice	–	–	60.61	–	–	–	52.42	–
Inpatient hospital	1526.8	–	720.5	–	1382.6	–	653.6	–
Institutional	–	65.31	–	195.7	–	55.92	–	167.1
Medical provider	–	91.47	–	–	–	71.25	–	–
Outpatient hospital	–	58.84	–	169.5	–	54.96	–	165.9
Prescribed medicine	197.3	39.10	–	214.1	204.4	40.41	–	220.6

Cells without an estimate indicate that parameter was not selected in the final model.

Table 20. Ratio of BRR standard error estimates to TSE standard error estimates for model terms in 0-12 month analysis

	Intercept	Months	$\sqrt{\text{Months}}$	$\sqrt{\min(\text{Months},6)}$
Total	–	–	0.848	–
By payer				
Medicare	–	–	0.885	–
Non-Medicare	–	0.969	–	0.980
Total private	–	0.919	–	0.913
Total public	–	–	0.916	–
Out-of-pocket	–	0.994	0.946	–
Medicaid	–	0.875	–	–
Private insurance	–	0.904	–	0.922
All HMO	–	–	0.938	–
By service				
Dental	–	1.017	–	–
Facility	–	1.059	–	–
Home health	–	0.941	–	0.909
Hospice	–	–	0.865	–
Inpatient hospital	0.906	–	0.907	–
Institutional	–	0.856	–	0.854
Medical provider	–	0.779	–	–
Outpatient hospital	–	0.934	–	0.979
Prescribed medicine	1.036	1.034	–	1.030

Cells without a ratio indicate that parameter was not selected in the final model.

Of the 28 parameter estimates in the models for terminal year medical expenditures across all the categories, variance estimates were lower using the BRR versus the TSE method in 23 of them; the other 5 had higher variance estimates with the BRR. For those parameters with lower variances using BRR, the reductions in standard error ranged from 1% to 22%. Four of these had less than a 5% reduction, 12 were in the range of 5-10% reduction, 6 were in the range of 10-20% reduction, and a single parameter had just over a 22% reduction in standard error as compared to TSE. Of those with a higher variance with the BRR method, 4 had less than a 5% increase in standard error, with a single parameter having a nearly 6% increase in standard error versus TSE. For each medical expenditure category all the parameters for that category either had reduced variance or increased variance. Three of the 5 parameters with increased variance came from a single category, prescribed medicine.

Table 21. Standard error estimates of terminal year expenditures in 0-12 month analysis, TSE method, BRR method, and their ratio

	TSE	BRR	Ratio[a]
Total	1278.8	1084.1	0.848
By payer			
Medicare	1108.0	980.3	0.885
Non-Medicare	820.8	778.2	0.948
Total private	623.5	566.3	0.908
Total public	1151.8	1054.9	0.916
Out-of-pocket	494.9	511.3	1.033
Medicaid	397.9	348.1	0.875
Private insurance	334.9	298.4	0.891
All HMO	267.5	251.0	0.938
By service			
Dental	21.22	21.63	1.019
Facility	497.9	527.0	1.058
Home health	245.0	228.1	0.931
Hospice	210.0	181.6	0.865
Inpatient hospital	1195.8	1079.8	0.903
Institutional	409.3	364.8	0.891
Medical provider	316.9	246.8	0.779
Outpatient hospital	371.0	328.2	0.885
Prescribed medicine	170.6	175.3	1.028

a Ratio is BRR estimate over TSE estimate

As with the parameter estimates, the variance estimates for the BRR tended to be lower than those from the TSE method. Of the 18 categories, 14 had reduced variance estimates using the BRR, corresponding mostly to those categories that had lower parameter estimate variances under BRR. Of the 4 categories with a higher variance estimate under BRR, 3 of them also had higher parameter estimate variances using BRR. The sole category that had lower parameter variance estimates but a higher variance estimate for the 12-month estimate of terminal medical expenditures was the out-of-pocket category. Of the categories with lower variance estimates for terminal year medical expenditures using BRR, 6 had a reduction of 5-10%, 7 had a reduction of 10-20%, and 1 had a reduction of over 22% in standard error using BRR versus TSE.

8.1.2 Based on the 6-18 month analysis

BRR and TSE standard errors for the parameter estimates in the 6-18 month analyses of medical expenditures are presented in Table 22. The ratios between the BRR and TSE standard error estimates for the parameters in these models are found in Table 23. Standard errors using both methods of variance estimation and the ratio of BRR standard error to TSE standard error for the 12-month estimate of terminal medical expenditures for all analyzed categories using the 6-18 month data are given in Table 24.

Table 22. Standard error estimates for model terms in 6-18 month analysis, TSE method and BRR method

	TSE			BRR		
	Intercept	Months	$\sqrt{\text{Months}}$	Intercept	Months	$\sqrt{\text{Months}}$
Total	5850.3	526.4	–	5364.2	477.4	–
By payer						
Medicare	5151.3	475.9	–	4577.5	413.7	–
Non-Medicare	3618.4	–	1102.3	3617.7	–	1105.4
Total private	2503.1	–	768.3	2713.6	–	832.2
Total public	5577.1	511.7	–	4935.5	447.6	–
Out-of-pocket	2204.6	–	686.0	2053.2	–	648.7
Medicaid	2175.2	–	687.5	2126.4	–	671.7
Private insurance	666.5	55.31	–	713.4	61.09	–
All HMO	1475.1	–	443.5	1347.9	–	401.9
By service						
Dental	86.63	–	28.04	92.01	–	28.92
Facility	3088.6	–	967.6	3095.8	–	978.9
Home health	694.7	–	213.6	630.8	–	195.7
Hospice	1317.9	–	421.5	1339.4	–	419.1
Inpatient hospital	3370.6	312.5	–	2997.7	276.1	–
Institutional	1307.0	112.3	–	1336.8	111.8	–
Medical provider	1178.6	115.7	–	1221.4	118.4	–
Outpatient hospital	774.9	72.07	–	731.7	70.26	–
Prescribed medicine	7569.0	655.1	4471.9	7367.1	623.1	4303.9

Cells without a ratio indicate that parameter was not selected in the final model.

Table 23. Ratio of BRR standard error estimates to TSE standard error estimates for model terms in 6-18 month analysis

	Intercept	Months	$\sqrt{\text{Months}}$
Total	0.917	0.907	–
By payer			
Medicare	0.889	0.869	–
Non-Medicare	1.000	–	1.003
Total private	1.084	–	1.083
Total public	0.885	0.875	–
Out-of-pocket	0.931	–	0.946
Medicaid	0.978	–	0.977
Private insurance	1.070	1.105	–
All HMO	0.914	–	0.906
By service			
Dental	1.062	–	1.031
Facility	1.002	–	1.012
Home health	0.908	–	0.916
Hospice	1.016	–	0.994
Inpatient hospital	0.889	0.884	–
Institutional	1.023	0.996	–
Medical provider	1.036	1.023	–
Outpatient hospital	0.944	0.975	–
Prescribed medicine	0.973	0.951	0.962

Cells without a ratio indicate that parameter was not selected in the final model.

For 22 of the 37 parameter estimates in the models for terminal year medical expenditures across all the categories, variance estimates were lower using the BRR versus the TSE method, while 11 parameter estimates had higher variance estimates using the BRR; the remaining 4 had negligible differences between the two variance estimates (less than a .5% difference). For those parameters with lower variances using BRR, the reductions in standard error ranged from 0.5% to 13%. Seven of these had less than a 5% reduction, 9 were in the range of 5-10% reduction, and 6 were in the range of 10-20% reduction in standard error as compared to TSE. Of those with a higher variance with the BRR method, 6 had less than a 5% increase, 4 were in the range of a 5-10%

increase, and a single parameter had a just over 10% increase in standard error versus TSE.

In most of the medical expenditure categories, the parameters in their models either had consistently reduced or consistently increased variance estimates with the BRR method as compared to the TSE method. For example, for Medicare expenditures the ratio between the BRR and TSE standard errors for both the intercept and linear in months terms were less than 1, 0.889 and 0.869, respectively. And for total private expenditures the ratio for both the intercept and square root in months term were greater than 1, 1.084 and 1.083, respectively.

Only the hospice category had parameters where one increased under BRR and the other decreased, however, the difference between the two methods was relatively minor for both parameters (a 1.6% increase for the intercept and a 0.6% decrease for the square root in months term under the BRR). In the facility and institutional categories, one of the parameters in the final model had an increased variance estimate under the BRR while the other parameter's variance estimates were negligibly different between the two methods. While for the non-Medicare expenditure category, both parameters had essentially the same standard error estimate under both methods.

Table 24. Standard error estimates of terminal year expenditures in 6-18 month analysis, TSE method, BRR method, and their ratio

	TSE	BRR	Ratio[a]
Total	1526.1	1409.3	0.923
By payer			
Medicare	1371.6	1214.6	0.886
Non-Medicare	642.7	544.3	0.847
Total private	482.3	423.7	0.879
Total public	1451.5	1316.5	0.907
Out-of-pocket	398.7	383.2	0.961
Medicaid	411.6	349.7	0.850
Private insurance	203.6	200.1	0.983
All HMO	291.0	274.1	0.942
By service			
Dental	23.29	23.51	1.009
Facility	552.0	487.2	0.883
Home health	168.7	145.6	0.863
Hospice	291.1	248.4	0.853
Inpatient hospital	956.2	896.7	0.938
Institutional	294.7	258.5	0.877
Medical provider	386.1	361.1	0.935
Outpatient hospital	237.8	248.0	1.043
Prescribed medicine	146.8	137.1	0.934

a Ratio is BRR estimate over TSE estimate

Of the 18 categories, 16 had reduced variance estimates using the BRR, while the remaining 2 had increased variance estimates under the BRR. Interestingly, most of the categories with increased parameter variance estimates using the BRR method had lower variance estimates for the 12-month terminal year estimate for expenditures. This was due to larger negative covariances between parameter estimates of the model using the BRR method as compared to the TSE method (data not shown), reducing the standard error of the predicted value at one year. For example, if our model gives $\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 m$, then since $Var(\hat{Y}) = Var(\hat{\beta}_0) + m^2 Var(\hat{\beta}_1) + mCov(\hat{\beta}_0, \hat{\beta}_1)$, a larger negative estimate of covariance between $\hat{\beta}_0$ and $\hat{\beta}_1$ using BRR can make the overall BRR estimate of variance of $\hat{Y}$ smaller even if the BRR variance estimates of $\hat{\beta}_0$ and $\hat{\beta}_1$ at $m = 12$ are higher than when using TSE. Only the dental category had both parameter and 12-month expenditure estimates with increased variance estimates under the BRR. For similar reasons, a single category, outpatient hospital expenditures, had lower variance estimates for parameters with a higher variance estimate for the terminal year estimate under the BRR.

Of the categories with lower variance estimates for terminal year medical expenditures using BRR, 2 had a reduction of less than 5%, 6 had a reduction of 5-10%, and 8 had a reduction of 10-20% in standard error using BRR versus TSE. Of the 2 categories with a higher variance estimate under BRR, the standard error for the terminal year estimate for dental expenditures was just under 1% higher while for outpatient hospital expenditures it was around 4% higher.

8.2 Discussion and conclusions

Similar to the Chowdhury (2013) study looking at the differences between the BRR and TSE methods in the MEPS data set, the BRR method tended to produce lower variance estimates than the TSE method, particularly when looking at the terminal year estimates across all the medical expenditure categories considered in this study.

Within this study, qualitatively, for parameter estimates, in the 0-12 month analysis, a higher number of parameter estimates had reductions in the size of the variance of the estimates using the BRR as compared to the 6-18 month analyses, with 82% of the parameters having lower BRR variances versus 59%, respectively. The number of categories with lower variances under the BRR for terminal expenditure estimates was similar in both the 0-12 and 6-18 month analyses, with 78% being lower in the 0-12 month and 89% in the 6-18 month models.

Generally reductions from BRR versus TSE were lower in the 0-12 month analyses than in the 6-18 month analyses, this may represent that the weights in the 0-12 month analyses (all MCBS subjects for each year 2006-2013) were, on average, lower (mean 3,361) compared to those in the 6-18 month analyses (mean 5,318) (those enrolled in the MCBS for at least 3 years with year of death 2006-2013), likely due to lower sample sizes in certain raking categories in the latter. Higher weights may introduce variance due to the higher variance of the weights themselves (Chowdhary 2013). This was reflected in the data with the 0-12 month weights having an SD of 1,236 as compared with the SD of the weights in the 6-18 month data of 1,979.

Unfortunately, unlike in the Chowdhary (2013) study, base weights and the adjustments used on both the base weights and BRR replicate weights were unavailable, so it was not possible to look at how the adjustments affected the differences between the BRR and TSE variances. This also meant it was not possible to look at the correlation between the expenditure variables considered and the variables used in the raking adjustments. Since higher correlation with raking adjustment variables was associated with higher reductions in the BRR variances estimates in Chowdhary (2013), lack of correlation might explain some of the variables with similar or higher variance estimates using the BRR method versus the TSE method.

The expenditure categories were examined for outliers, particularly with high weights, as presences of these outliers were associated with higher variances using the

BRR versus the TSE method (data not shown). Unlike Chowdhary's (2013) results, outliers did not seem to be associated with higher variances under the BRR. While we did not look at this analytically, from our qualitative observations, some categories with outliers had lower variances, and some without had higher variances (data not shown). However, these outliers were not particularly strong outliers in most of these cases or did not have particularly high weights. The one category that did fit the Chowdhary (2013) findings was dental, which had a couple of extreme outliers with decently high weights, and had consistently higher variances for both parameters and 12-month terminal estimates.

Chowdhary's (2013) study focused solely on proportions and means of variables in the MEPS data, while this study is using more complicated models. Future research into differences between replication methods like the BRR and the TSE method will hopefully look at other models, like the linear models used in this study.

9 COVARIATE ANALYSES OF SELECTED TERMINAL YEAR MEDICAL EXPENDITURES USING THE 6-18 MONTH DATA

In order to assess the effect various covariates for a select set of terminal year medical expenditures, two different covariate analyses were performed using the 6-18 month data, first with each covariate considered separately, then by fitting all the covariates together and performing a backwards selection process (these analyses will be described later). The 6-18 month data were used because the 12-month mark falls in the middle of the data range rather than the edge as with the 0-12 month data. In order to facilitate the effect of these covariates on the 12-month estimates of expenditures, we centered the data so that the intercept was at the 12-month prior to death mark. For linear models this was performed by subtracting 12 from the variable for the number of months alive. Since we cannot take square roots of negative numbers, for the square root models, the variable created for these models subtracted the square root of 12 from the square root of the number of months alive.

For these analyses, only the total, Medicare (including Medicare HMO expenditures), total private (includes private insurance [self-purchased, employer-based, and unknown-payer], private HMO, and out-of-pocket expenditures), and Medicaid expenditure categories were considered, as these were the main categories of expenditure.

The nominal covariates considered in the analyses were age, geographical region, race, and sex. The age at death variable used was categorized as: 65-69, 70-74, 75-79, 80-84, and 85+ years. For geographical region, the US census regions were utilized: Midwest, Northeast, South, and West. Preliminary frequency analyses found very few beneficiaries located outside of the 50 U.S. states (all of whom resided in Puerto Rico), so that the majority of the blocks by age, race, and sex in this geographical region contained no beneficiaries. As a result, beneficiaries located in Puerto Rico were excluded from analysis. A similar issue occurred within the racial categories, sample sizes for races other than Black or White were small, so blocks by age, US census region, and sex contained few (often 0, 1, or 2) terminal beneficiaries within these racial classifications. Therefore, it was decided to further limit these analyses to only those who were classified as either White or Black by the MCBS. Finally, the covariate of calendar year was fit as a continuous variable in order to investigate whether there was any linear trend by year in these expenditure categories after adjusting for inflation (all expenditures were given in 2013 dollars regardless of calendar year).

9.1 Demographics of the sample for the covariate analyses

The demographics on sex, race, age at death category, and US Census region for the sample of decedent beneficiaries used in the covariate analyses are noted below in Table 25. Sample weighted means and standard deviations of medical expenditures for decedents in each expenditure category, unadjusted for months alive, as well as the average duration of backwards follow-up from death are given in given in Table 26.

Table 25. Demographics for decedent beneficiaries from the 6-18 month data for covariate analyses

Total decedent beneficiary records, n	2486
Sex, n (%)	
Female	1366 (55.0)
Male	1120 (45.0)
Race, n (%)	
White	2222 (89.4)
Black	264 (10.6)
Age at death category, n (%)	
65-69	144 (5.8)
70-74	204 (8.2)
75-79	347 (14.0)
80-84	551 (22.2)
85+	1240 (49.9)
US Census region, n (%)	
Midwest	602 (24.2)
Northeast	488 (19.6)
South	989 (39.8)
West	407 (16.4)
Calendar year, n (%)	
2006	377 (15.2)
2007	319 (12.8)
2008	324 (13.0)
2009	325 (13.1)
2010	287 (11.5)
2011	284 (11.4)
2012	289 (11.6)
2013	281 (11.3)

Table 26. Mean (SEM)[a] for death backwards follow-up duration and unadjusted expenditures by category	
Duration of follow-up, months	12.07 (0.07)
Expenditures[b,c]	
Total	67743 (1443.9)
By payer	
Medicare	44180 (1217.2)
Non-Medicare	23563 (539.6)
Total private	14131 (432.2)
Total public	53041 (1323.1)
Out-of-pocket	10123 (381.8)
Medicaid	7609 (335.5)
Private insurance	4008 (217.4)
Total HMO	3089 (262.5)
By service	
Dental	180.1 (24.25)
Facility	13849 (457.4)
Home health	2122 (152.0)
Hospice	4407 (242.9)
Inpatient hospital	23372 (867.0)
Institutional	6276 (259.9)
Medical provider	10169 (401.3)
Outpatient hospital	4191 (263.3)
Prescribed medicine	3177 (109.4)

a SEMs estimated using BRR with Fay's method
b Values are given in 2013 dollars

9.2 Single covariate analyses

Twelve-month estimates were determined by fitting the final model selected in the primary 6-18 month analysis (linear terms for months in total and Medicare, square root of month terms for total private and Medicaid) with two additional parameters used to account for the covariate effect on the slope and the other for the intercept.

For the linear single covariate models this means that the model fit was $Y = \beta_0' + \alpha_i + \beta_1'(m - 12) + (\alpha\beta)_i(m - 12)$ for the nominal covariates of age, race, US Census region, and sex, with α_i and $(\alpha\beta)_i$ representing the additional effects on the intercept and slope based on the i-th level of the covariate of interest, respectively. For the linear trend in year, the model, with year as the only covariate, fit was $Y = \beta_0' + \alpha y + \beta_1'(m - 12) + (\alpha\beta)y(m - 12)$, with y being the number of years since 2006 (since 2006 was the start year), and α and $(\alpha\beta)$ representing the additional linear effects on the intercept and slope based on the year, respectively. As before, Y is the expense of interest and m is the number of months of follow-up based on the number of days alive in the calendar year of death and the year prior for those who died in June or earlier of the calendar year of death using the midpoint of the month.

For square root single covariate models, the model fit was $Y = \beta_0' + \alpha_i + \beta_1'\left(\sqrt{m} - \sqrt{12}\right) + (\alpha\beta)_i\left(\sqrt{m} - \sqrt{12}\right)$ for the nominal covariates and $Y = \beta_0' + \alpha y + \beta_1'\left(\sqrt{m} - \sqrt{12}\right) + (\alpha\beta)y\left(\sqrt{m} - \sqrt{12}\right)$, for the year covariate. Due to the recentering of the data the intercept effects of β_0' and α_i (or α) were used to determine the effect of the covariates on the terminal expenditure estimates at 12 months, with the slope effects of β_1' and $(\alpha\beta)_i$ (or $(\alpha\beta)$) serving as tuning parameters for the model. For the categorical variables of age, race, region, and sex, parameter estimates for the levels of the covariate were determined based on setting one level as a baseline and determining the differences from that baseline level for the other levels of the covariate. These baseline levels were 85+ for age at death, White for race, the West US Census region for region, and Male for sex.

9.2.1 Results

Estimates (with standard errors) for total terminal year expenditures for each level of the categorical covariates can be found in Table 27. These are converted back into overall expenses for each level by adding in the intercept and adjusting for the variance and covariances of all terms to get the overall standard error. Additionally, the first row for each covariate gives the p-value for the overall test of that covariate. These estimates and p-values are based on fitting that single covariate without adjusting for any of the others. Finally, the last row of the table gives the yearly change in the total terminal year expenditure estimate (again not adjusted for any other covariate), with standard error, and p-value for the effect of year. Similar tables are given for terminal year Medicare, private, and Medicaid expenditures can be found in Table 28, Table 29, and Table 30, respectively.

Table 27. Estimates of covariate associations with total terminal year medical expenditures[a], single covariate analysis

Model term	Estimate	Standard Error	p-value[b]
Age at death			0.078
65-69 years	73763	6627	
70-74 years	75891	6196	
75-79 years	68954	5011	
80-84 years	67199	2706	
85+ years	63162	1500	
Race			0.0014
Black	83811	5478	
White	65454	1375	
Census region			<0.0001
Midwest	64253	2499	
Northeast	84866	3270	
South	62852	2002	
West	62613	4330	
Sex			0.24
Female	69010	1973	
Male	65565	2073	
Yearly change[c]	-6.34	651.6	0.99

a Values in 2013 dollars
b p-value gives test of overall model effect
c Per year increase

Table 28. Estimates of covariate associations with terminal year Medicare expenditures[a], single covariate analysis

Model term	Estimate	Standard Error	p-value[a]
Age at death			<0.0001
65-69 years	53888	6153	
70-74 years	56030	5662	
75-79 years	51406	4404	
80-84 years	44450	1967	
85+ years	35346	1038	
Race			<0.0001
Black	63393	4893	
White	41604	1167	
Census region			0.0030
Midwest	41122	2031	
Northeast	54311	3084	
South	41791	1611	
West	41204	3837	
Sex			0.61
Female	43292	1770	
Male	44604	1696	
Yearly change[c]	-0.97	571.7	>0.99

a Values in 2013 dollars
b p-value gives test of overall model effect
c Per year increase

Table 29. Estimates of covariate associations with total terminal year private expenditures[a], single covariate analysis

Model term	Estimate	Standard Error	p-value[a]
Age at death			<0.0001
65-69 years	11864	1520	
70-74 years	11612	1824	
75-79 years	10607	761.9	
80-84 years	13794	849.3	
85+ years	17060	732.4	
Race			<0.0001
Black	8922.7	873.1	
White	14913	477.1	
Census region			0.012
Midwest	15455	842.4	
Northeast	16830	1292	
South	12620	702.8	
West	13499	1057	
Sex			0.77
Female	14140	655.2	
Male	14421	644.6	
Yearly change[c]	45.86	191.2	0.81

a Values in 2013 dollars
b p-value gives test of overall model effect
c Per year increase

Table 30. Estimates of covariate associations with terminal year Medicaid expenditures[a], single covariate analysis

Model term	Estimate	Standard Error	p-value[a]
Age at death			0.0051
65-69 years	7159	1725	
70-74 years	6352	881.8	
75-79 years	5792	898.5	
80-84 years	7283	917.6	
85+ years	9256	508.5	
Race			0.023
Black	10219	1109	
White	7414	381.2	
Census region			0.0002
Midwest	5739	579.7	
Northeast	12316	1290	
South	6942	403.7	
West	6880	827.6	
Sex			<0.0001
Female	10343	560.3	
Male	4750	421.6	
Yearly change[c]	-64.22	154.7	0.68

a Values in 2013 dollars
b p-value gives test of overall model effect
c Per year increase

9.2.2 Discussion and conclusions

Taken singly, age at death was a significant factor in terminal year Medicare, private, and Medicaid expenditures, but not for total terminal year medical expenditures. Increasing age at death generally was associated with lower terminal year Medicare expenditures, peaking at $56,030 for those between 70-74 years old and falling to $35,346 in those 85+. This may be due to a decrease in expensive and potentially heroic measures taken near death in older patients. A reverse pattern was seen in private expenditures, with terminal year costs similar in the three age at death ranges between 65-79, with a low of $10,607 in the 74-79 age range, rising to $13,794 for 80-84 years of age, and finally to $17,060 for those 85 and older. This may be associated with increasing use of long-term care facilities at older ages which are not covered by Medicare and must generally be paid for privately (unless the beneficiary also qualifies for Medicaid or VA benefits).

There appears to be a V-shaped trend in Medicaid expenditures by age at death, with the lowest values in the 74-79 year-old age range. Significant differences were seen between the peak value of $9,256 for those aged 85 and older and for the low value of $5,792 in those 74-79 and the $6,352 of those 70-74 (no significant difference between the latter two).

Race had significant association in all the expenditure categories analyzed. For total, Medicare, and Medicaid expenditures, Black terminal year of life expenditures were significantly more than those for Whites. Overall spending was $18,356 higher for Blacks as compared to Whites, with that difference basically due to $21788 more in Medicare expenditures. Additionally, Medicaid expenditures for Black decedents was $2,804 higher than that of Whites. These were offset by $5,990 fewer private expenditures by Blacks as compared to Whites.

There were significant regional differences in all four expenditure categories. However, for all but private expenditures these were wholly driven by larger expenditures in the Northeast with all other regions being statistically similar. Expenditures for those in the Northeast were $20,613 higher for Total, $12,520 higher for Medicare, and $5,374 higher for Medicaid, than the next highest region, Midwest for total, and South for Medicare and Medicaid. In contrast, regional differences in private expenditures were found to be significantly higher in the Midwest compared with the

South (a difference of $2,385). The Northeast was also significantly higher than both the South (a difference of $4,210) and the West (a difference of $3,331).

Sex differences were negligible in total, Medicare, and private terminal year expenditures. However, there was a large sex difference in Medicaid expenditures, with last year of life expenditures for decedent women $5,593 higher than that of men perhaps due to last year of life being in long term care facilities more often for women than for men.

A linear trend by year in terminal CPI adjusted year expenditures was not seen in any of these categories, indicating that medical expenditures in these categories matched the CPI between the years 2006-2013. This result is interesting in light of the generally higher costs after adjustment for inflation in these measures compared to the results from 1992-1996 as seen in Hoover et al (2002), as shown in Section 6.5.2 (page 69).

9.3 Multiple covariate analysis

For the multiple covariate analysis, 12-month estimates were determined by fitting the final model selected in the primary 6-18 month analysis. Therefore, linear terms for months in total and Medicare were used and square root of month terms for total private and Medicaid were used. In these models two parameters were employed for each covariate and their 2-way interaction terms, one for differing slopes and the other for differing intercepts. Thus the model fit was

$$Y = \beta_0 + \beta_1 m' + \text{main effects} + \text{interactions} + \text{main effects} * m' + \text{interactions} * m'$$

where Y was the expenditure category of interest, m' was $(m - 12)$ for linear models and $\left(\sqrt{m} - \sqrt{12}\right)$ for square root models (to center the data at 12 months) with m the number of months of follow-up based on the number of days alive in the calendar year of death adding on the last six months of the year prior for those who died in June or earlier of the calendar year of death using the midpoint of the month. The list of main effects is given below in Table 31 and the list of interaction terms is given below in Table 32. As in the single covariate analysis, year was included in the model in order to investigate whether there was any linear trend by year in these expenditure categories after adjusting for inflation (all expenditures were given in 2013 dollars regardless of calendar year), all other covariates were treated as categorical variables. Due to the lack of a main effect for year in the single covariate analyses and because of a limited number of degrees of freedom available, interactions with calendar year were not considered. Backwards model selection with a cutoff of p=0.01 was used to remove terms from the model. Main effects were removed from the model only if non-significant at the p=0.01 level and all interaction terms containing that main effect had already been removed via the backwards selection process. The intercept and slope effects and interactions were considered separately, that is, a covariate (or interaction) slope effect might be removed from the model even if the equivalent intercept effect remained, and vice versa.

Table 31. Main effects considered for multiple covariate analysis

Effect	Levels
Age at death	65-69, 70-74, 75-79, 80-84, 85+
Race	Black, White
US Census Region	Midwest, Northeast, South, West
Sex	Male, Female
Calendar year	0-7*

* Calendar year was fitted as a linear term based on the number of years after 2006

Table 32. Interaction terms considered for multiple covariate analysis

Interaction terms
Age at death * Race
Age at death * US Census Region
Age at death * Sex
Race * US Census Region
Race *Sex
US Census Region * Sex

9.3.1 Results

For total terminal year expenditures, of the 24 terms initially included in the model, the selection process eliminated 14, eight of which were intercept effects and six of which were slope effects. The intercept terms centered at 12 months (with final model p-values) and breakdown of the differences (with standard errors) in 12-month terminal medical expenditures due to these intercept effects can be seen in Table 33. The baseline estimate of total expenditures is based on the estimated expenditures for a beneficiary who was White, 85 or older, and living in the West U.S. Census Region. Since slope effects had no direct influence on the 12-month estimates, these terms (with final model p-values) and the slope parameter estimates (with standard errors) are nuisance parameters and will not be presented in the main text. However, information on these terms can be found in Table 39 in Appendix A.

Table 33. Estimates of multivariate model covariate associations with total terminal year medical expenditures[a]

Model term[b]	Estimate	Standard Error	p-value
Baseline[c]	55359	3451	<0.0001
Age at death, change from baseline			0.0065
65-69 years	12530	5160	
70-74 years	13535	5462	
75-79 years	6742	5455	
80-84 years	5391	3365	
85+ years	0	–	
Race, change from baseline			0.0012
Black	17442	5246	
White	0	–	
Census region, change from baseline			<0.0001
Midwest	2981	4202	
Northeast	23846	4455	
South	53.3	4170	
West	0	–	

a Values are in 2013 dollars
b Not included in the final model: Sex, Year
c The baseline estimate is for a White, 85+ year old decedent beneficiary living in the West US Census region, all other estimates in this table are for changes from this baseline value for that level of the given covariate

The variables selected for total terminal year Medicare expenditures came out the same as the one selected for total expenditures, though there were some minor differences in the order of removal. This finding is unsurprising as the 12-month estimated Medicare expenditures from the overall 6-18 month analysis is 66% of the terminal year estimate for total expenditures. The intercept terms centered at 12 months (with final model p-values) and breakdown of the differences (with standard errors) in terminal year Medicare expenditures due to these intercept effects can be seen in Table 34. As with the total, the baseline estimate for Medicare expenditures is based on the estimated expenditures for a beneficiary who was White, 85 or older, and living in the West U.S. Census Region. Slope effects (nuisance parameters) with final model p-values and parameter estimates with standard errors can be found in Table 40 in Appendix A.

Table 34. Estimates of multivariate model covariate associations with terminal year Medicare expenditures[a]

Model term[b]	Estimate	Standard Error	p-value
Baseline[c]	29294	2931	<0.0001
Age at death, change from baseline			<0.0001
65-69 years	18721	4941	
70-74 years	20785	5034	
75-79 years	16704	4657	
80-84 years	9841	2269	
85+ years	0	–	
Race, change from baseline			<0.0001
Black	20533	4766	
White	0	–	
Census region, change from baseline			<0.0001
Midwest	1933	3453	
Northeast	15228	4056	
South	316	3501	
West	0	–	

a Values are in 2013 dollars
b Not included in the final model: Sex, Year
c The baseline estimate is for a White, 85+ year old decedent beneficiary living in the West US Census region, all other estimates in this table are for changes from this baseline value for that level of the given covariate

For total private expenditures, of the 24 initially fitted terms, only 5 came out significant in the final model. None of the slope effects save the baseline slope effect for the square root of number of months alive remained in the final model. Of the four remaining intercept effects, one was the baseline intercept, two were the main effects of age and race, and the last was the interaction between age and race. The intercept terms centered at 12 months (with final model p-values) and breakdown of the differences (with standard errors) in terminal year private expenditures are seen in Table 35. In this model, the baseline estimate is based on the estimated private expenditures for a beneficiary who was White and 85 or older. Because of the inclusion of the age by race interaction term, in order to evaluate any trends in age by race, Table 36 contains point estimates for total terminal private expenditures for each level of age and race. Slope effects (nuisance parameters) with final model p-values and parameter estimates with standard errors can be found in Table 41 in Appendix A.

Table 35. Estimates of multivariate model covariate associations with total terminal year private expenditures[a]

Model term[b]	Estimate	Standard Error	p-value
Baseline[c]	17882	768.1	<0.0001
Age at death, change from baseline			0.0017
65-69 years	-6710	1835	
70-74 years	-5869	2432	
75-79 years	-6689	1221	
80-84 years	-3264	1092	
85+ years	0	–	
Race, change from baseline			0.0063
Black	-9545	1246	
White	0	–	
Age at death by Race interaction, change from baseline			0.0038
65-69 years, Black	13824	5090	
70-74 years, Black	6957	3189	
75-79 years, Black	3675	1936	
80-84 years, Black	4132	2451	
85+ years, Black	0	–	

a Values are in 2013 dollars
b Not included in the final model: US Census region, Sex, Year
c The baseline estimate is for a White, 85+ year old decedent beneficiary, all other estimates in this table are for changes from this baseline value for that level of the given covariate or for the level of the interaction term

Table 36. Estimates of total terminal year private expenditures[a] by race and age, multiple covariate analysis

Race	Black	White
Age at death, years		
65-69 years	15450	11172
70-74 years	9424	12013
75-79 years	5323	11193
80-84 years	9205	14618
85+ years	8336	17882

a Values are in 2013 dollars

Of the initial 24 model terms, 8 terms remained in the final model when considering terminal year Medicaid expenditures. Of those remaining, 6 were intercept effects (intercept, all 4 main effects, and the interaction effect between age and race), and the other 2 were slope effects (baseline slope of square root of months, square root of months by sex). The intercept terms centered at 12 months (with final model p-values) and breakdown of the differences (with standard errors) in terminal year Medicaid expenditures are seen in Table 37. As before, in this model, the baseline estimate is based on the estimated private expenditures for a beneficiary who was White, Male, 85 or older, and in the West Census region. Because of the inclusion of the age by race interaction term, Table 38 gives a two-way table of differences in terminal Medicare expenditures by age holding race, census region, and sex fixed, in order to see trends in age by race. Slope effects (nuisance parameters) with final model p-values and parameter estimates with standard errors can be found in Table 42 in Appendix A.

Table 37. Estimates of multivariate model covariate associations with terminal year Medicaid expenditures[a]

Model term[b]	Estimate	Standard Error	p-value
Baseline[c]	4341	937.6	<0.0001
Age at death, change from baseline			0.0012
65-69 years	1406	2127	
70-74 years	-1728	1231	
75-79 years	-1875	1116	
80-84 years	-274.8	1113	
85+ years	0	–	
Race, change from baseline			0.8912
Black	7611	2381	
White	0	–	
Census region, change from baseline			0.0007
Midwest	-826.9	1036	
Northeast	4957	1430	
South	-18.12	905.8	
West	0	–	
Sex, change from baseline			<0.0001
Female	5276	733.1	
Male	0	–	
Age at death by Race interaction, change from baseline			0.0065
65-69 years, Black	-14617	3863.8	
70-74 years, Black	-6319	3186	
75-79 years, Black	-8065	3640	
80-84 years, Black	-8294	3225	
85+ years, Black	0	–	

a Values are in 2013 dollars

b Not included in the final model: Year

c The baseline estimate is for a White, Male, 85+ year old decedent beneficiary living in the West US Census region, all other estimates in this table are for changes from this baseline value for that level of the given covariate or for the level of the interaction term

Table 38. Differences in estimates relative to 85+ age category of terminal year Medicaid expenditures[a] by race, multiple covariate analysis

Race	Black	White
Age category, years		
65-69 years	-13212	1406
70-74 years	-8047	-1728
75-79 years	-9940	-1875
80-84 years	-8569	-274.8
85+ years	0	0

a Values are in 2013 dollars

9.3.2 Discussion and conclusions

In the analyses of total and Medicare expenditures in the last year of life, the remaining intercept effects of age, race, and census region significantly affect the 12-month estimate of total terminal year expenditures. The ranges in the total last year of life expenditures ran from $55,359 for a white, 85+ year-old living in the West, to $110,182 for a black, 70-74 year old living in the Northeast. For Medicare expenses the range for last year of life expenditures was $29,294 for a white, 85+ year-old living in the West, to $85,840 for a black, 70-74 year old living in the Northeast.

Notable is that after adjustment for the other variables, sex was removed as a significant factor in total and Medicare medical expenditures in the last year of life. For the analysis of Medicare, this finding fits with a prior analysis by Shugarman et al (2004), that found that after adjustment for age and other factors, the effect of sex on terminal year Medicare expenditures became statistically insignificant, with the decreased costs of dying at older ages explaining the lower estimates for women versus men when the estimates of these costs were unadjusted.

Total adjusted medical expenditures in the last year of life generally decline with rising age, with a peak in the 70-74 year old age range, $13,535, higher than in those 85 and older (the lowest age category). Two large drop-offs are seen in total adjusted expenditures, between the 65-69 and 70-74 age categories combined and the 75-79 and 80-84 age categories combined (a drop of $6793 between those 70-74 and 75-79 years old) and then from the 75-84 categories and 85+ age category (a decline of $5391 between those 80-84 and those 85 and older). These decreases in total adjusted medical expenditures as related to age at death are potentially due to a decreased push for treatment for older patients (Levinsky et al 2001). But of interest would be to see if this could be due to differences in causes of death by age (with less expensive causes for older age, in particular) since the rates of chronic conditions and the number of co-morbidities increase with age (Atella et al 2018). Unfortunately, data on causes of death were unattainable for this study but would be worth investigating in future inquiries.

As with total adjusted expenditures, adjusted terminal year of life Medicare expenditures decline with rising age from a peak in the 70-74 year old age range $20,785 higher than the low point in the 85+ age range, consistent with prior studies (Shugarman et al 2004). Unlike in the total adjusted expenditure category, the differences between those in the 75-79 year old category and the 80-84 year category are both significantly higher than the baseline 85+ category. Also there is also no significant decline between the 70-74 year-old decedents and the 75-79 year-old decedents, with the first big drop off of $6,863 happening later between the 75-79 year old range and the 80-84 year old range, with a further significant drop of $9,841 to the 85+ range. While this trend likely reflects the overall decline in terminal year of life medical expenditures with rising age, the decline in adjusted Medicare expenditures in the last year of life is also much steeper than the same decline seen in the total expenditure category.

Unlike prior work in the area (Shugarman et al 2004), these covariate adjustments differences in terminal year of life adjusted Medicare expenditures between Blacks and Whites were independently significant. On average, black beneficiaries had about $20,533 more in terminal year of life adjusted Medicare expenditures than those of white beneficiaries. But the difference in total adjusted expenditures between Blacks and

Whites was slightly lower than that found in the adjusted Medicare expenditures with black beneficiaries having only $17,442 more in terminal year of life total adjusted expenditures than those of white beneficiaries.

This analysis did not find much adjusted difference in terminal year of life total or Medicare expenditures between the Midwest, South, and West. However, the Northeast census region had significantly higher costs than the other regions, with terminal year of life total adjusted expenditures $23,846 higher than a beneficiary of the same age and race in the West census region. Similarly, for adjusted terminal year of life Medicare expenditures, the Northeast had additional expenditures about 50% of the baseline costs ($15,228) relative to a beneficiary of the same age and race in the West census region.

The adjusted differences in blacks and whites and between the Northeast and the rest of the country may be because of a difference in urban concentrations between these populations and regions, respectively with more Blacks and Northeasterners being in urban areas. Shugarman et al (2004), were able to adjust for urban/non-urban metropolitan/rural county and they found no significant difference between terminal year of life Medicare expenditures between blacks and whites with adjustment for this and other factors (like age). Their paper, however, had no adjustment for general geographic region, so it is also possible that this effect was missed in their analysis. It is possible that differences in health care laws between the regions could account for some of these differences.

Like the total and Medicare adjusted expenditure models, terminal year of life adjusted private expenditure estimates were unaffected by sex. However, unlike these models, these adjusted estimates were also not significantly affected by census region.

Additionally, while race and age at death were significant effects alone, there was also a highly independently significant interaction between race and age at death. Generally, this translated to higher terminal year of life adjusted private expenditures for Whites than Blacks, except in the 65-69 year age range. Terminal year of life adjusted private expenditures for Whites from 65-79 are relatively similar, increasing with age beyond that point (increasing $3,425 from the 75-79 range to the 80-84 range and then a further $3,264 to the 85+ age range). This trend in Whites is likely due to increasing reliance on long-term care facilities in the aging population, costs that are not covered by Medicare, but need to be paid for privately, or, if qualified, using Medicaid or VA benefits.

Unlike the trend in Whites, in Blacks there is no clearly discernable trend in terminal year of life private expenses by age at death, with an initial adjusted decline in terminal year of life private expenditures in the 70s with a subsequent rise into the 80s and beyond. Here, increasing Medicaid expenses with respect to age in Blacks, which is likely due to increasing costs for long-term care (which accounts for a large portion of Medicaid expenditures in the elderly) (CMS 2018), may account for this lack of a clear trend in terminal of life private expenditures. Estimates for terminal year of life private expenditures ranged from $5,323 for a black, 75-79 year-old to $17,882 for a white, 85+ year old.

Unlike the other categories analyzed, terminal year adjusted Medicaid expenditures did have an independently significant adjusted sex association, with adjusted expenditures $5,276 higher for women than compared to men, all else being equal. While, data from the 2019 Current Population Survey shows that, in 2018, 11.1% of all women 65 and over were below the poverty threshold compared to 8.1% of men 65 and older (United States Census Bureau 2019), this net difference of 3% in the poverty rate is unlikely to explain much of this adjusted difference unless there is a large association between poverty and higher Medicaid costs.

This difference instead are likely due to increased need for nursing facilities in women as compared to men. Freedman et al (2016) showed that the age-adjusted percentage of those 65 and older with severe activity limitations (defined as being limited in 3 or more personal care activities or in a nursing facility) is higher in women as compared with men (9.8% versus 7.0% in 2004 and 10.2% versus 7.3% in 2011, respectively). Additionally, the number of remaining years with severe disability for those 65 and older is higher for women in all age groups. Furthermore, the percentage of women 65 and older living alone is higher than that of men, 32% versus 18%, and more likely to be widowed, 37% versus 12% (Stepler 2016).

As with all three previous expenditure categories, there is not much adjusted difference between the Midwest, South, and West census regions for terminal year of life Medicaid expenditures. However, again the Northeast region has significantly higher adjusted terminal year of life Medicaid expenditures, all else being equal, with, for example, these adjusted terminal year of life Medicaid expenditures being $4,957 more in the Northeast than in the West census region.

Amongst Whites, there are no clear differences in terminal year of life Medicaid expenditures by age at death, with the highest terminal year of life expenditures happening in the 65-69 year age range and the lowest in the 75-79 age range. For Blacks, on the other hand there is a discernable upward adjusted trend, with those from 65-69 having the lowest terminal year of life adjusted Medicaid expenditures, \$13,212 less than those 85 and older, followed by those between 70-84, ranging from \$8,047 to \$9,940 less than those 85 and older, with a sharp increase of \$8,569 for those 85 and older relative to those between the ages of 80 and 84. Similar to the case of terminal year of life private expenditures for Whites (where there was no trend amongst Blacks), the differences here may be due to increased long-term facility usage with increasing age, something often covered by Medicaid. This upward trend in terminal year of life Medicaid expenditures in Blacks compared with the upward trend in terminal year of life private expenditures in Whites, may point to increased need for Medicaid to cover long-term care in elderly Blacks.

For terminal year of life Medicaid expenditure estimates ran from an (albeit impossible) negative number of \$-2,087 for a black, 65-69 year old, man from the Midwest to \$22,185 for a black, 85+ year old, woman from the Northeast. Of note is that for any 65-69 year old black man outside of the Northeast, the estimate for Medicaid expenditures in the last year of life is negative. However, the 95% confidence intervals for the negative estimates all contain \$0, and are likely due to small numbers of male black descendants aged 65-69.

As in the single covariate analysis of year, no linear trend by year in terminal year of life expenditures was seen in any of these categories, indicating that adjusted terminal year of life medical expenditures in these categories matched the CPI between the years 2006-2013. As mentioned above, this result is interesting in light of the generally higher costs after adjustment for inflation in these measures compared to the results from 1992-1996 as seen in Hoover et al (2002).

10 SUMMARY

The first goal of this study was to expand on previous models of last year of life terminal medical expenditures, with updates to the basic modeling procedure, but application to a newer set of data. We did this by performing the 0-12 month analysis using the 2006-2013 MCBS data. We improved upon previous models by eliminating the m^2 (where m is months of follow up before death) term which was unnecessary in the light of it never being included in any models in Hoover et al (2002), due to it modeling declines in spending in the months closer to death. Instead, because expenditures often rise only in the last few months of life (Davis et al 2016), we decided to look at a different term that takes this into account, the $\sqrt{\min(m, 6)}$ term, allowing for the acceleration in expenditures to only happen in the last 6 months. Moreover, we utilized a previously unused (but not new) procedure to estimate variances in this model, the BRR, versus the previous standard TSE method. The BRR method of variance estimation is robust as is the TSE method, and while simulation studies have shown that it often has larger bias for variance estimation (which may not be true for variances of regression coefficients), it has been shown to tend to have better coverage properties (Wolter 2007) in spite of the fact that the variance estimate of BRR is often lower than that of TSE as we observed here and summarize below.

One of the issues with the 0-12 month analysis and others like it (as in Hoover et al 2002, De Nardi et al 2016, and French et al 2018), is that the value of interest, the terminal year expenditure estimate, lies on the very edge of the range of data used. Generally it is preferable to have this estimate in the middle of the range of data as that typically results in better variance properties. Our approach to address this was to create a model from last 6 to 18 months of life. To do this we considered decedent beneficiaries with MCBS data in the year prior to death, and added that data to those decedents with less than 6 months of follow-up in their calendar year of death.

Unfortunately, weights for this group of decedents were not available (but will be in future MCBS years). However, we did have access to weights for those decedents with data from at least 2 years prior to the year of death and were able to restrict the above analysis to this groups with a small loss in sample size. The results from this analysis were encouraging with the vast majority of terminal year expenditure estimates from the 6-18 month models being close to those estimated from the 0-12 month analysis. Additionally, while the standard errors were often a bit higher for these estimates than in the 0-12 month data, much of this increase seems to be due to the significant decrease in the sample size. Adjustment for sample size found that for most of the estimates, the 6-18 month analysis would have had a much smaller variance as compared to the 0-12 month analysis had the sample sizes been the same.

During the analysis of these data that we and others have used to model terminal year of life medical expenditures, we discovered that starting in the 1995 MCBS, death dates were always set to the end of the month of the date of death, rather than having the actual date of death as in the 1992-1994 MCBS (in these years a handful of decedents' death dates were unknown and were set to the end of the month). Using these death dates, as they were, would result in invalid model specification, specifically intercept estimates would be too low and potentially significant when they should not be. While death rates in the US vary month to month, with higher death rates in the winter months (Xu 2019), we felt it reasonable, as others have shown (Law and Brookmeyer 1992), to assume a uniform distribution for time of death within the month, conditional on knowing the month of death, and so set the date of death for each decedent to the midpoint of the month of death. In order to test this empirically, we performed a sensitivity analysis on those years where we had the actual date of death for the vast majority of decedents, 1992-1994, by using the methods from the 0-12 month analysis on these years first using the given dates of death and then using the midpoint of the month of death. Results from this analysis indicated that using the midpoint of the month was reasonable.

Another motivation of the 6-18 month analysis was that we hypothesized that more of our models would be linear in time, rather than involving the square root of time. However, we found that in half of the categories, the models selected did not contain the linear term. We were interested in how much of an effect using a linear model, rather than the square root model would have on these categories. Refitting these models with a linear term generally did not cause much of an effect on modeled terminal year of life expenditures, other than slightly reducing the terminal year estimate (likely due to the central location of the estimate and the concavity of the square root function). We also fit the 6-18 month models that removed the intercept in cases where they were not significant and again found little difference in the terminal year of life estimates for those categories.

Because the one prior study using the MCBS that reported variances (Hoover et al 2002) utilized the TSE approach to estimate these variances and we used the BRR method in this paper, we decided to fit the models both ways in both the 0-12 and 6-18 month analyses and see what effect this would have on the variances for our parameters and our terminal year estimates. As far as we know, nothing in the literature has ever done this type of comparison using the MCBS. We found that while the variances for parameter estimates were generally lower for the BRR, especially in the 0-12 month analysis, this was by no means guaranteed. However, for the 12-month terminal year estimates, the BRR variance estimates were almost universally lower, and in a couple cases quite a bit lower. This lends support to utilizing this method for this type of analysis in any future studies.

Our final analyses utilized our 6-18 month data to determine the effects for the covariates of age at death, race, US census region, sex, and calendar year (with the last fitted as an continuous variable), to our knowledge the first analysis of this type. We did so by fitting each of the covariates individually and in a multiple covariate model with interactions using a backwards selection on the terms. When looking individually, we found that race and US census region were significantly associated with terminal year of life expenditures in all the payor categories we considered (total, Medicare, total private, Medicaid). Additionally, age at death was a significant factor in all but total terminal year expenditures. Only in Medicaid was there any significant sex difference and calendar year of death was insignificant in all the analyses.

When adjusting for multiple covariates, we found that age at death and race were independently significant across all four expenditure categories analyzed and US census region was significant in all but total private expenditures. Again, sex was an independently significant effect only in Medicaid spending and calendar year was not significant in any category.

11 FUTURE RESEARCH

Future research based on these analyses could be used to overcome some of the limitations of this study. First, obtaining exact death dates were cost prohibitive for this paper. With access to these data, the models could be slightly improved over using the midpoint of the month for the date of death and may result in better estimates and smaller variance estimates (albeit our sensitivity analysis in Section 7.1 on page 76 shows that such improvement would be limited).

The 6-18 month analysis can also be improved post-2016 due to changes in the MCBS data in 2015. Starting in 2016, 1-year sample and replicate weights will be available (these are unavailable in 2015 due to the MCBS not being released in 2014). These weights would cover anyone who had been in the MCBS for at least 2 calendar years (the year of death and the prior year). This would increase the sample size available for the 6-18 month analysis, relative to the sample used in this paper, as we only had 2-year weights available. These weights cover all those who had been in the MCBS for at least 3 calendar years (the year of death and the two prior years) and so we could not use any decedents with only 2 calendar years of data. An increased sample size should reduce the standard errors for the estimates in the 6-18 month analysis, potentially leading to them being lower more generally for the 6-18 month analysis relative to the 0-12 month analysis.

Unfortunately, the MCBS summary data by patient does not break down expenditures by payer and service together. If it were possible to look at the expenditure categories not only by payer or by service, but by both payer and service, this would allow for better conclusions for spending trends for each payer in the last 12 months of life, since there would be a better idea of the breakdown of by-service expenditures in decedents, rather than relying upon the NHE breakdowns by service and payer that include all those 65 and older.

Statistically, it would be of interest to replicate the analysis done in Chowdhury, where the TSE and BRR methods were contrasted at every step of adjustment of the sample and BRR replicate weights, starting from the initial base weights (inverse of selection probability) through all adjustments for demographic characteristics, nonresponse, and other design adjustments. Unfortunately, the MCBS provides only the final sample and replicate weights after all adjustments are made. With access to the full survey design or the adjustments to the weights at each stage of tweaking, the difference between the BRR variances and the TSE variances could be done at each stage. Additionally, factors used in the raking could be compared to the base results for correlation to see which correlate strongly with the outcome measure and could explain why certain results favored the BRR and others the TSE method for variance estimation.

With access to other demographic data sets, like death information, other covariates (beyond age at death, region, race calendar year of death and sex) could be considered in the multiple covariate analyses. Additional considerations could include urban/rural region, services available, cause of death, number of hospital beds in the region, number of physicians in the region, and local incomes.

12 GRAPHS

12.1 Estimation of terminal year expenditures

12.1.1 Graphs of regression curves for selected models in the 0-12 month analysis

Lines represent the fitted models; circles represent the averaged cumulative expenses for those with given months alive in calendar year of death. Shaded region about line represents pointwise 95% confidence band.

Figure 4. Regression curve for <u>total</u> terminal year of life medical expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

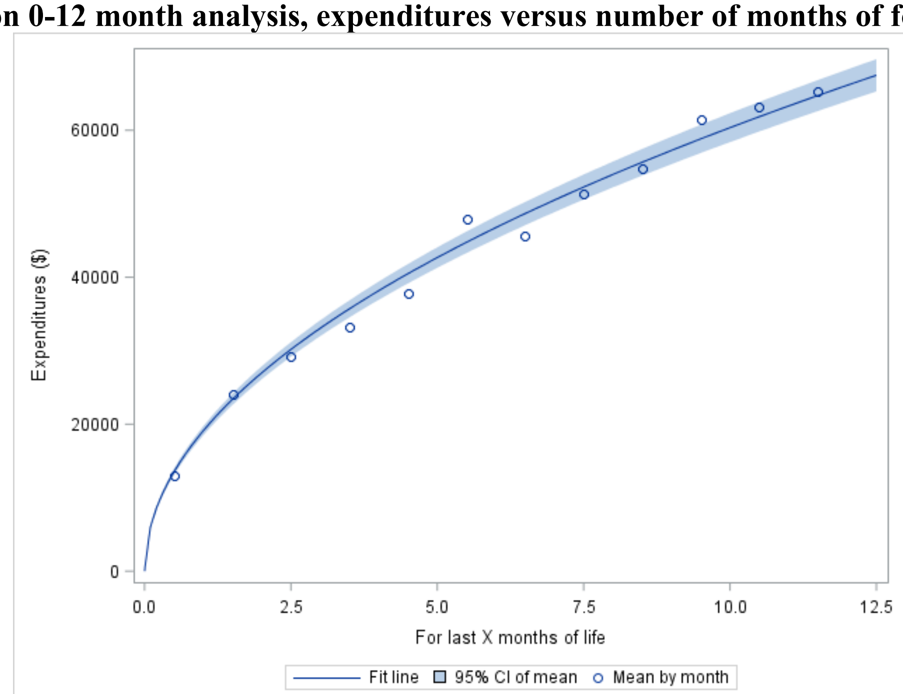


Figure 5. Regression curve for terminal year of life <u>Medicare</u> expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

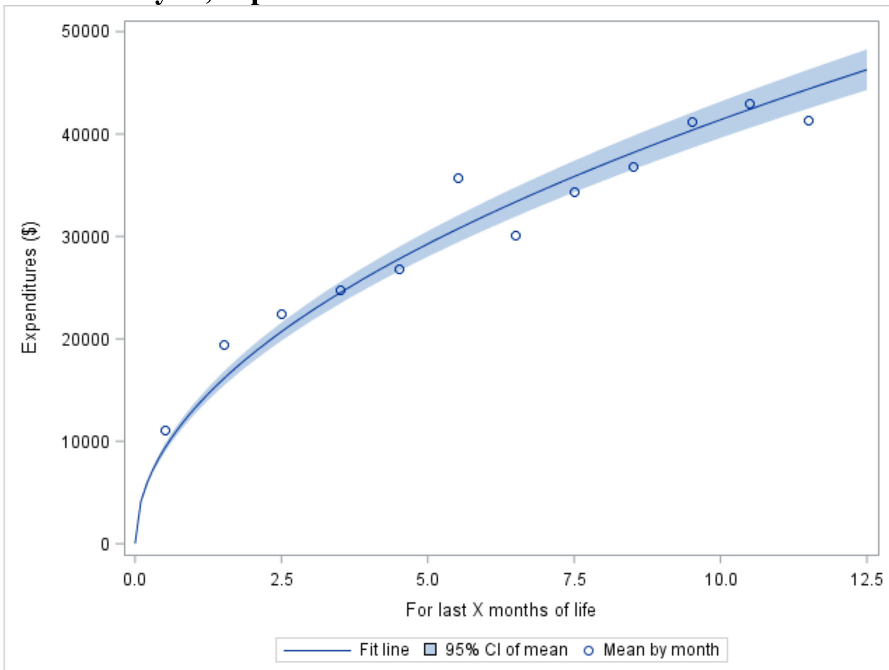


Figure 6. Regression curve for terminal year of life <u>non-Medicare</u> expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

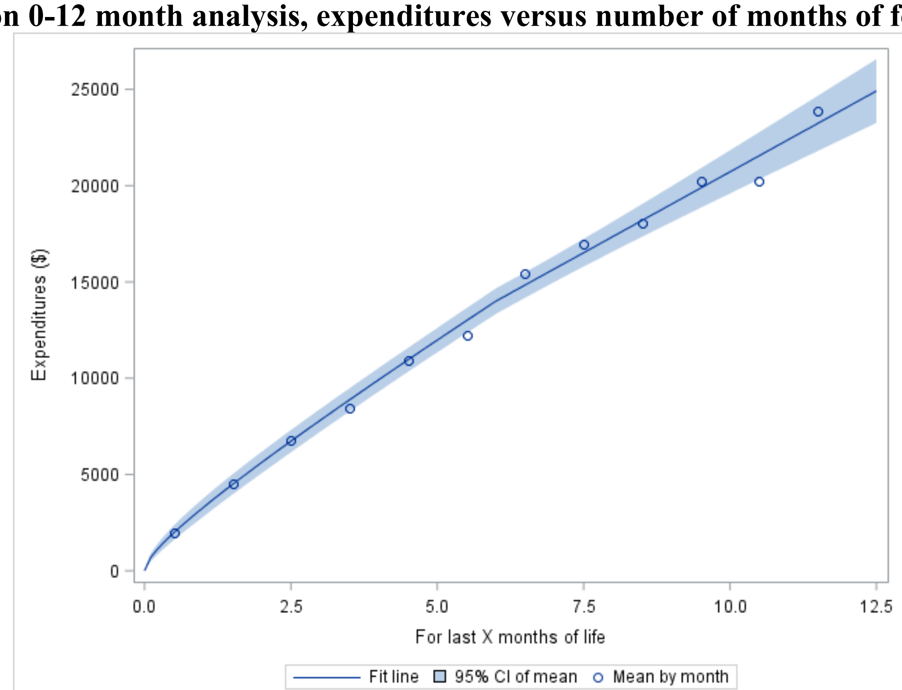


Figure 7. Regression curve for total terminal year of life private expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

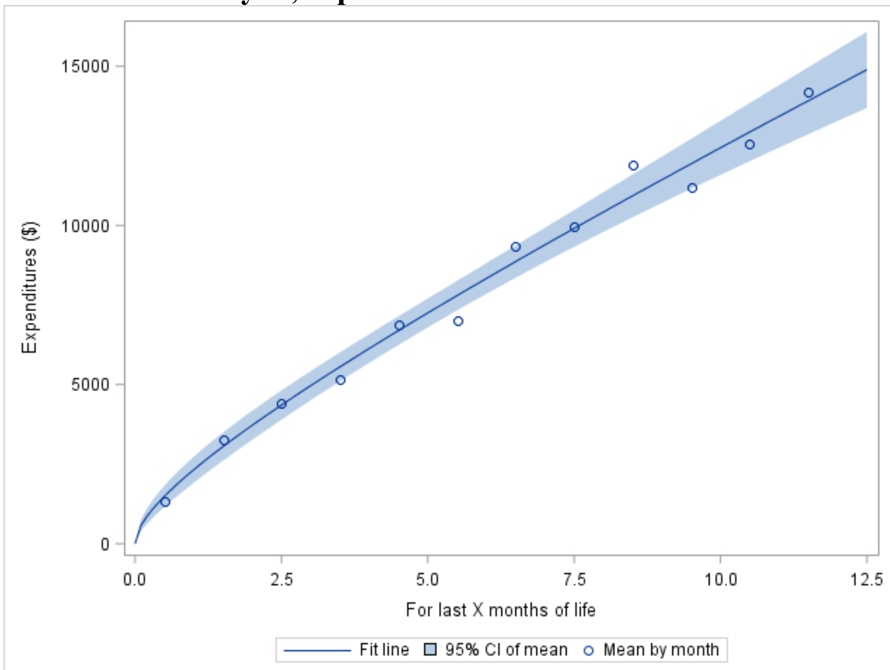


Figure 8. Regression curve for total terminal year of life public expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

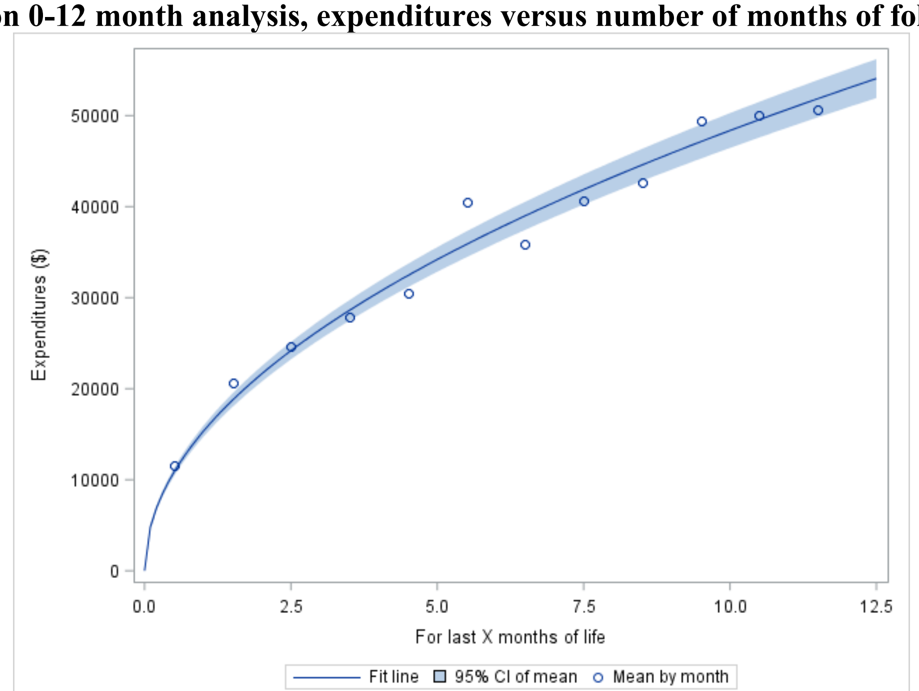


Figure 9. Regression curve for terminal year of life out-of-pocket expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

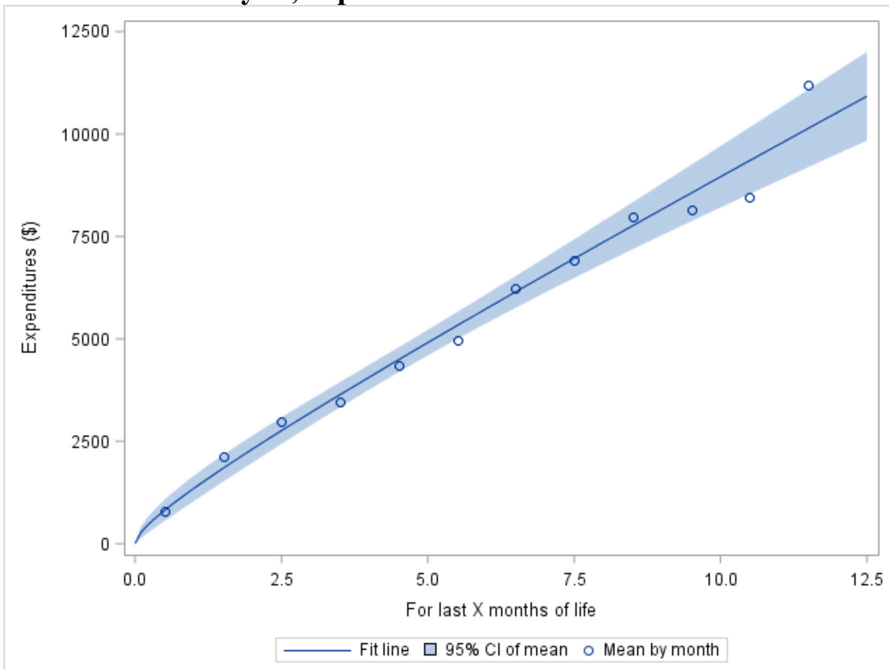


Figure 10. Regression curve for terminal year of life Medicaid expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

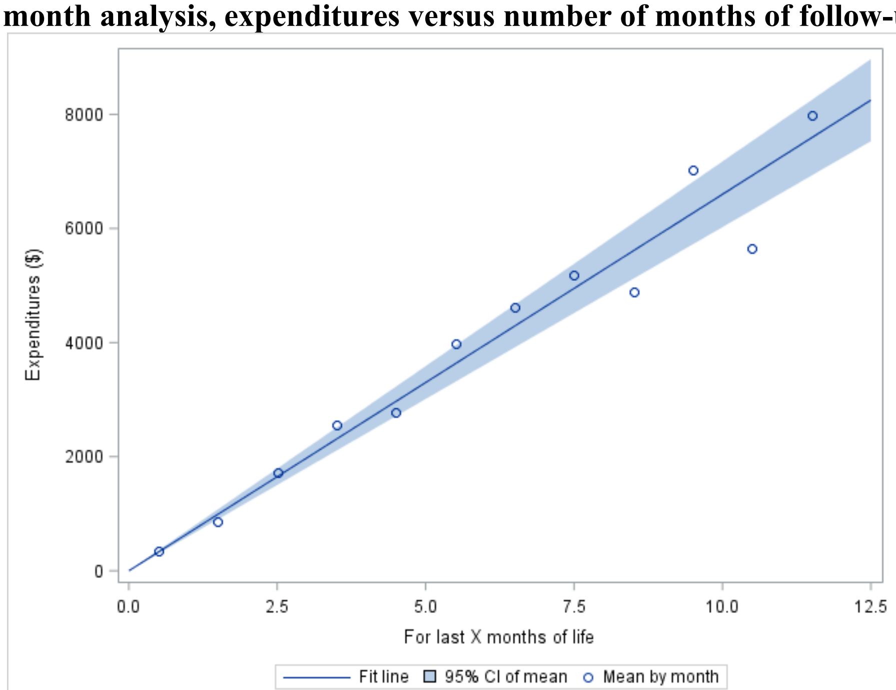


Figure 11. Regression curve for terminal year of life <u>private insurance</u> expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

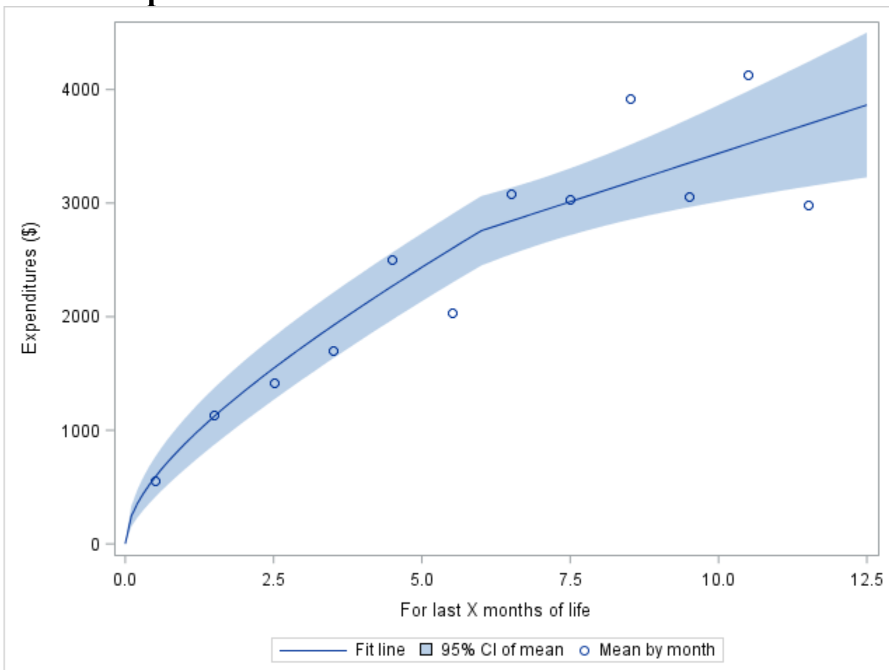


Figure 12. Regression curve for total terminal year of life <u>HMO</u> expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

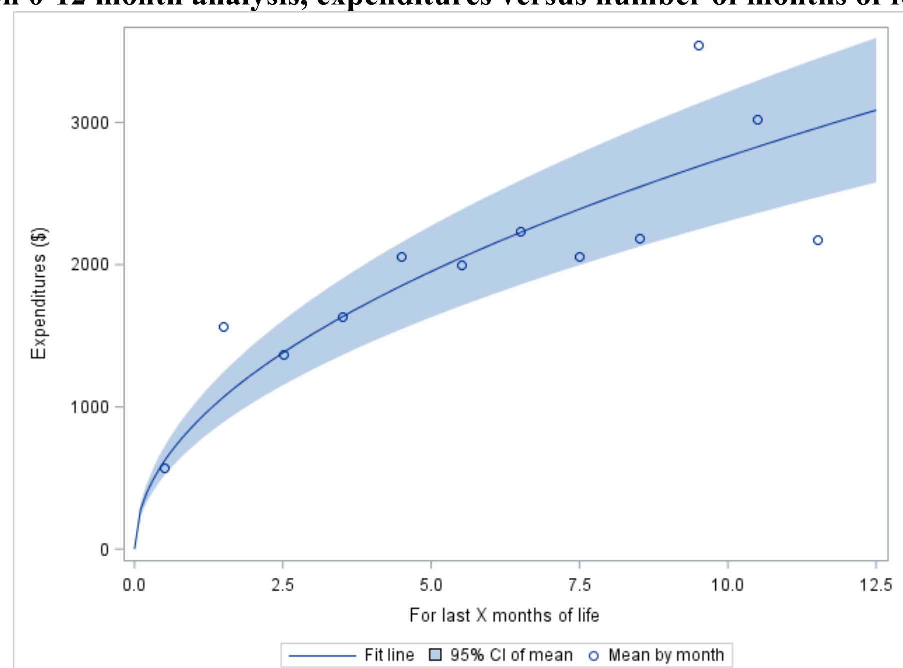


Figure 13. Regression curve for terminal year of life dental expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

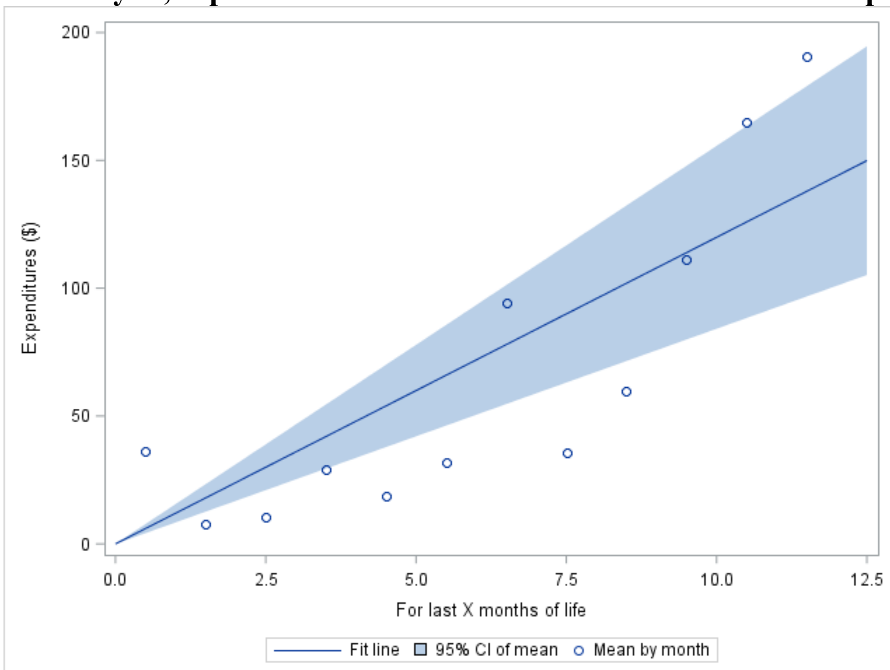


Figure 14. Regression curve for terminal year of life facility expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

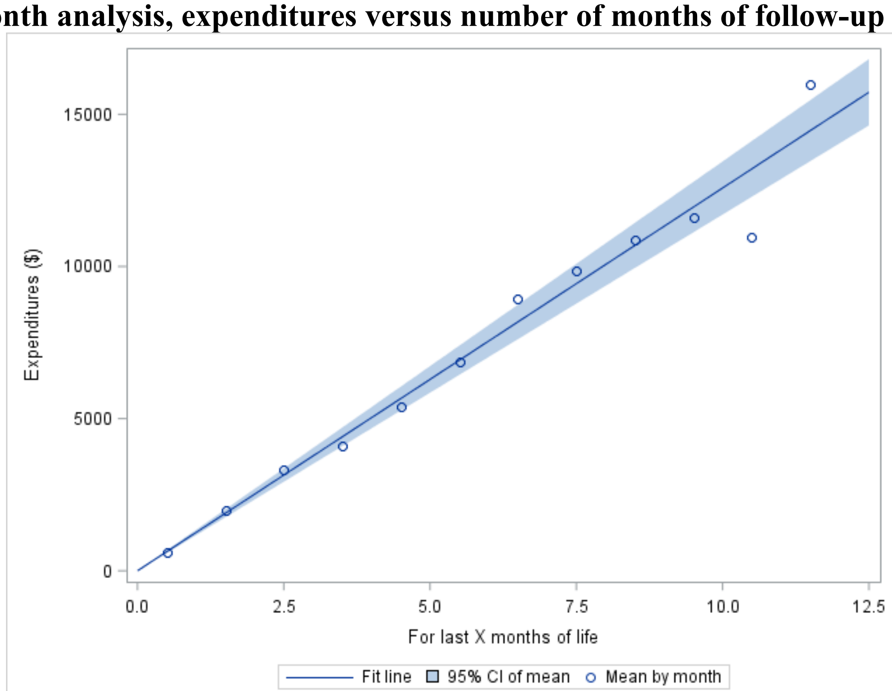


Figure 15. Regression curve for terminal year of life <u>home health</u> expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

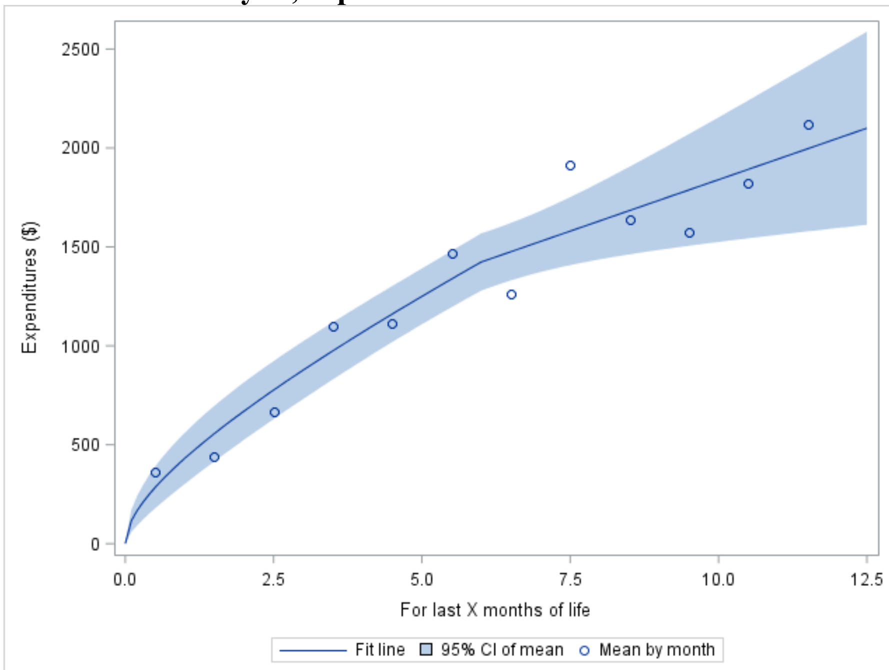


Figure 16. Regression curve for terminal year of life <u>hospice</u> expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

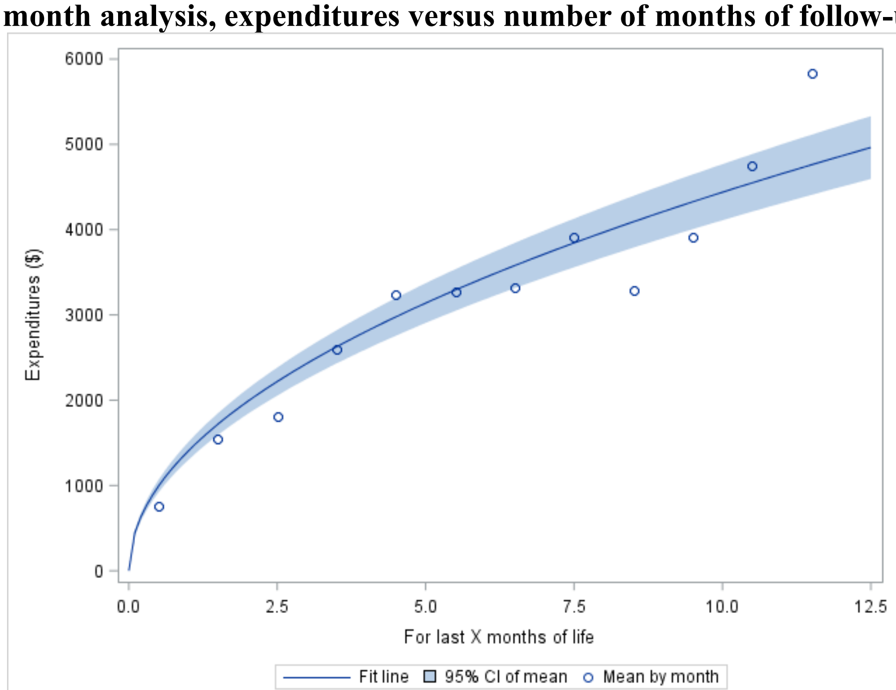


Figure 17. Regression curve for terminal year of life inpatient hospital expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

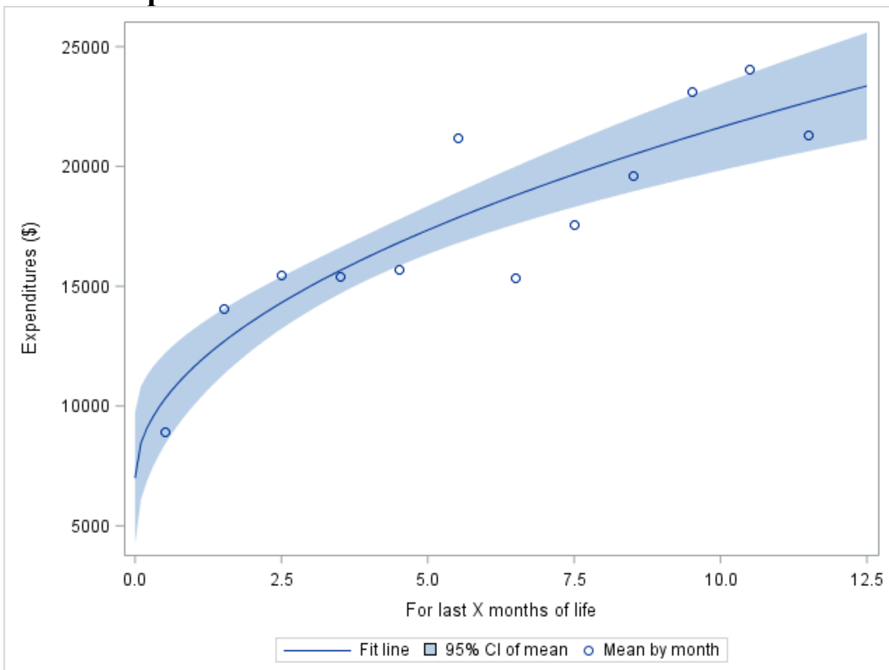


Figure 18. Regression curve for terminal year of life institutional expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

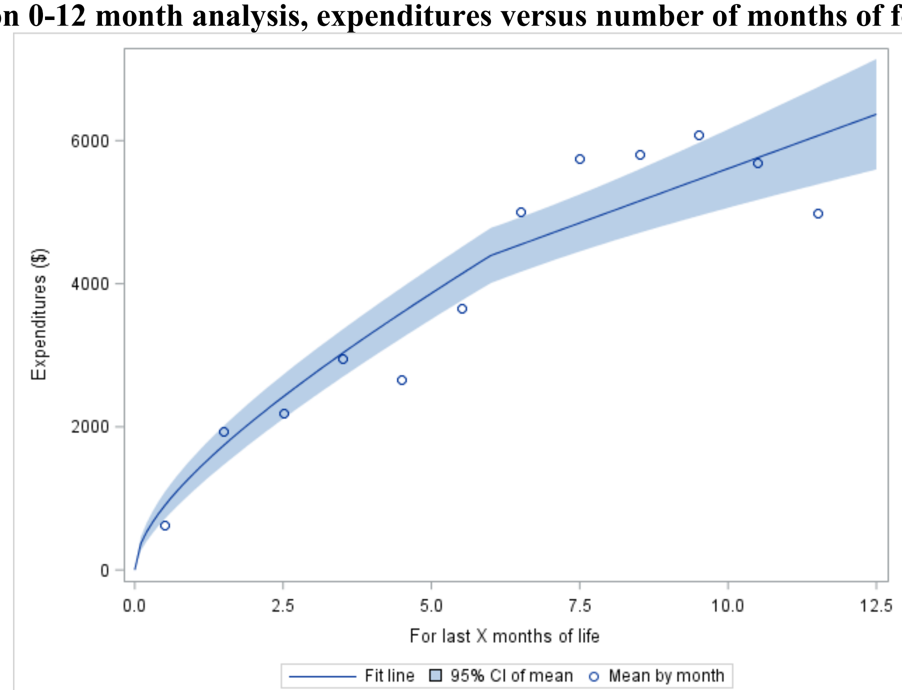


Figure 19. Regression curve for terminal year of life <u>medical provider</u> expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

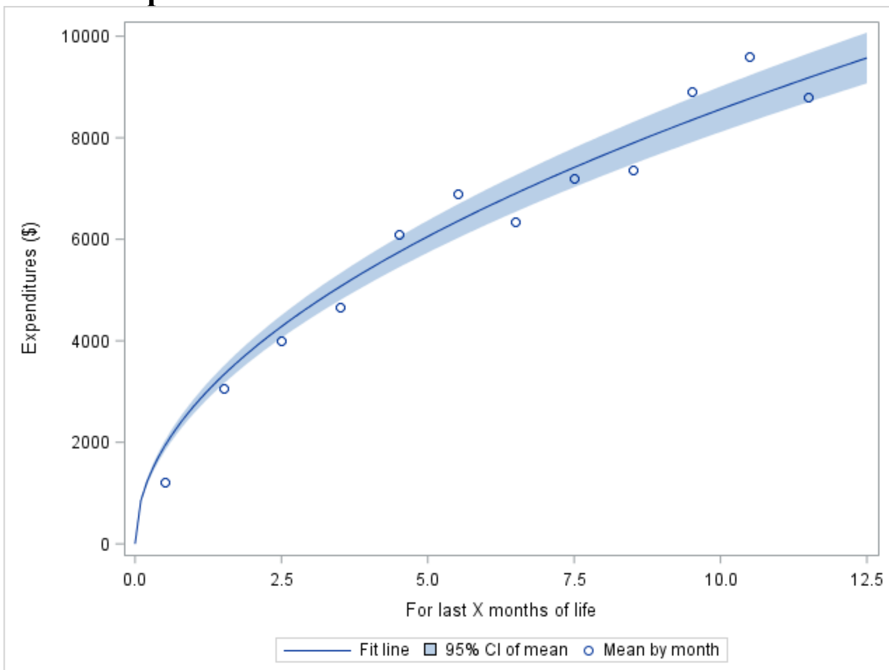


Figure 20. Regression curve for terminal year of life <u>outpatient hospital</u> expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up

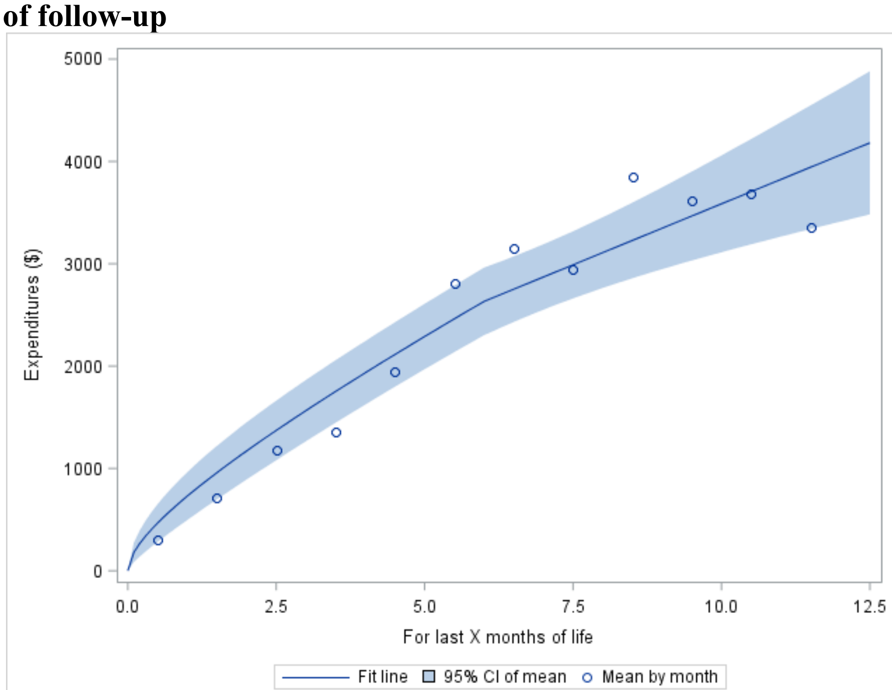
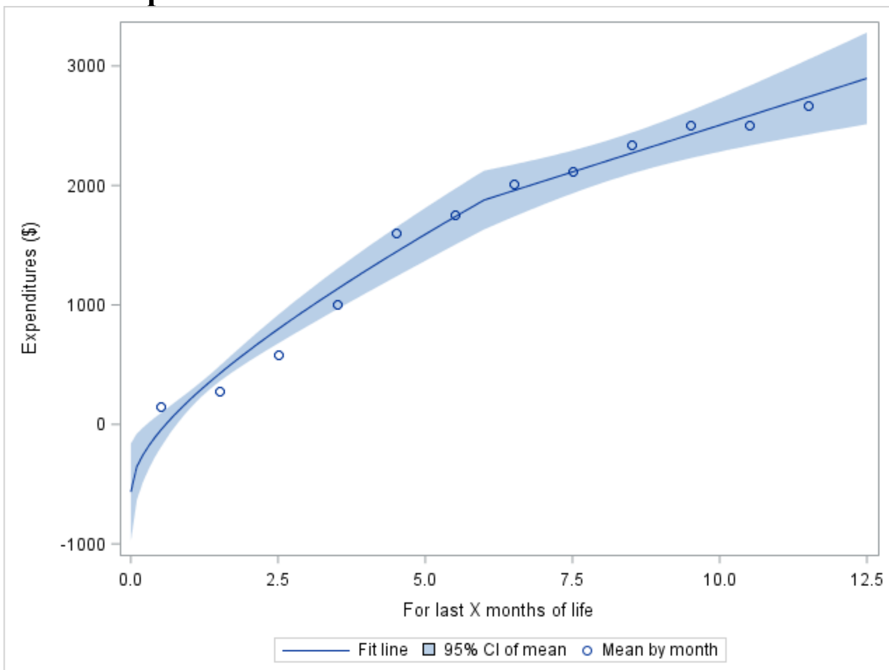


Figure 21. Regression curve for terminal year of life <u>prescribed medicine</u> expenditures based on 0-12 month analysis, expenditures versus number of months of follow-up



12.1.2 Graphs of regression curves for selected models in the 6-18 month analysis

Lines represent the fitted models; circles represent the averaged cumulative expenses for those with given months alive in calendar year of death. Shaded region about line represents pointwise 95% confidence band.

Figure 22. Regression curve for <u>total</u> terminal year of life medical expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

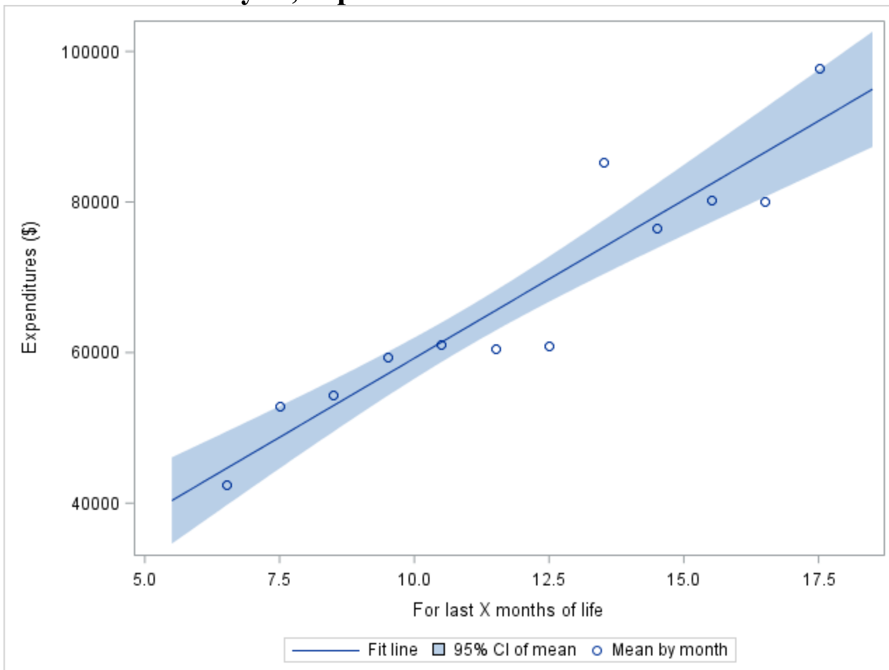


Figure 23. Regression curve for terminal year of life <u>Medicare</u> expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

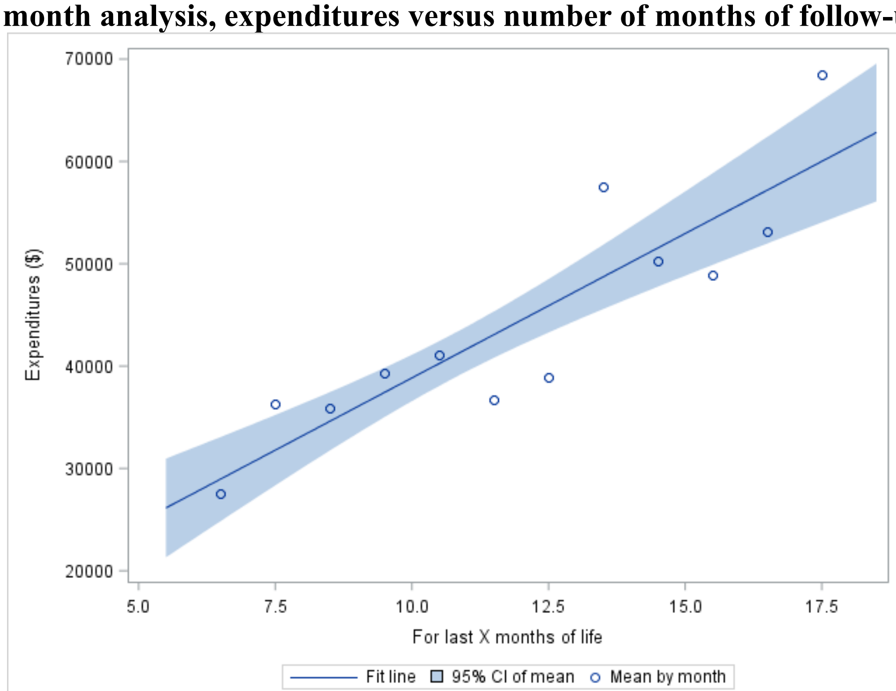


Figure 24. Regression curve for terminal year of life non-Medicare expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

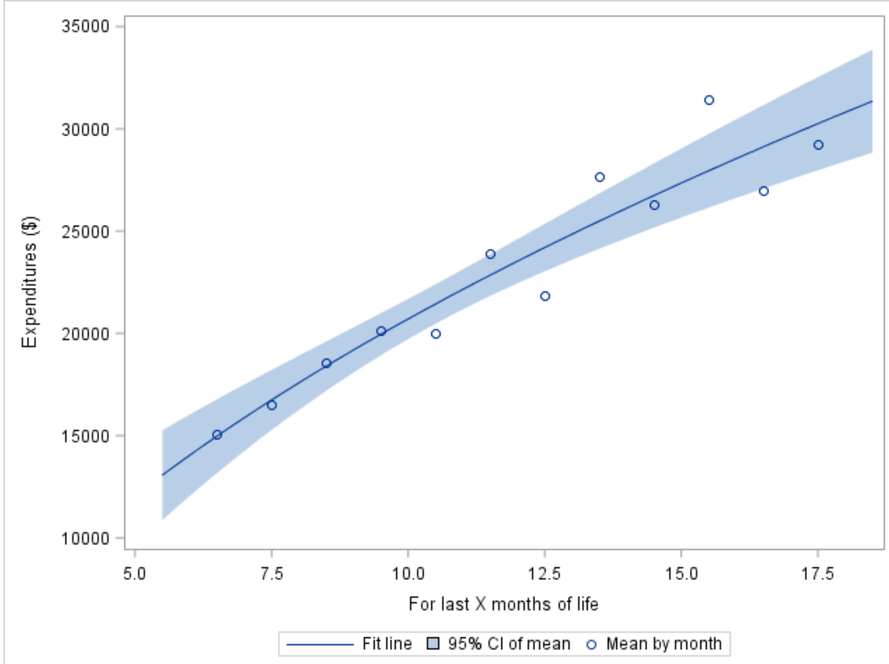


Figure 25. Regression curve for total terminal year of life private expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

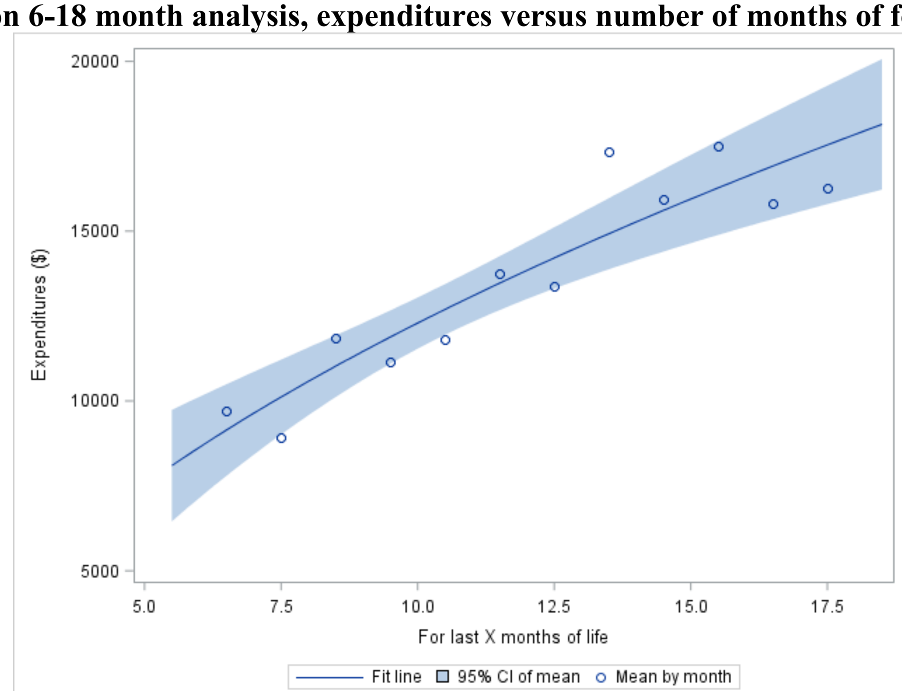


Figure 26. Regression curve for total terminal year of life public expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

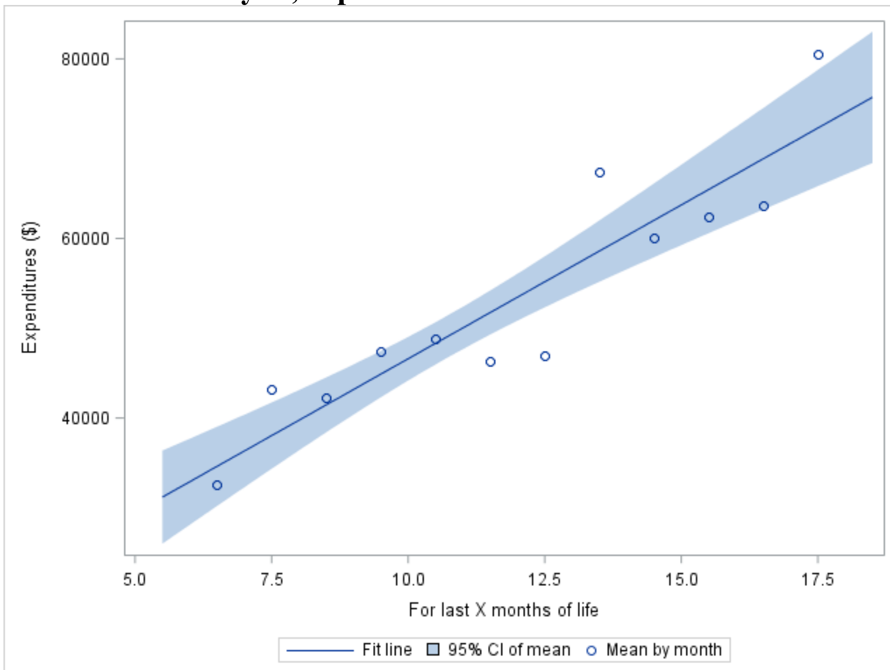


Figure 27. Regression curve for terminal year of life out-of-pocket expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

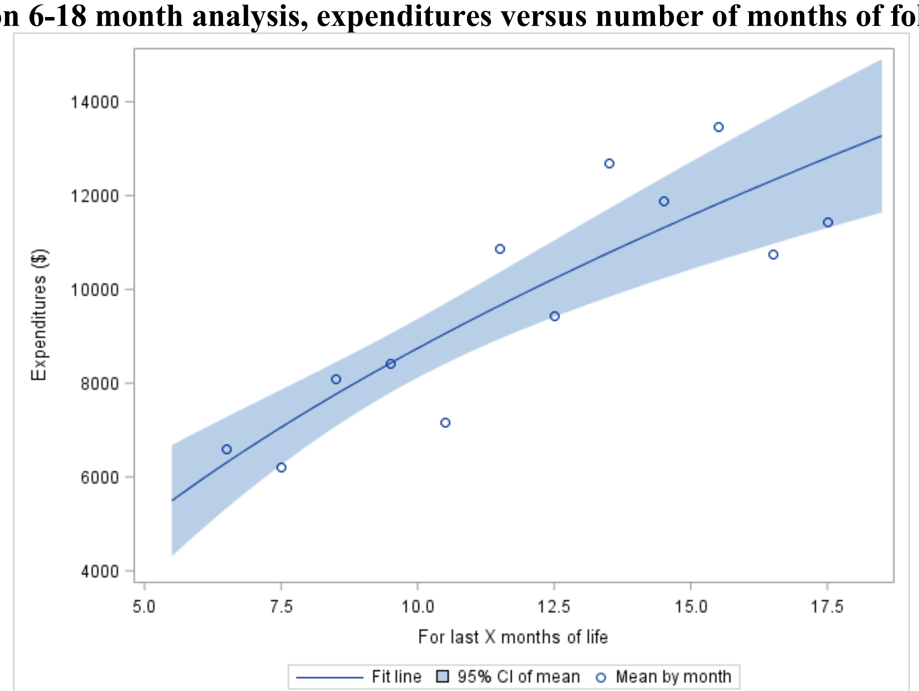


Figure 28. Regression curve for terminal year of life Medicaid expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

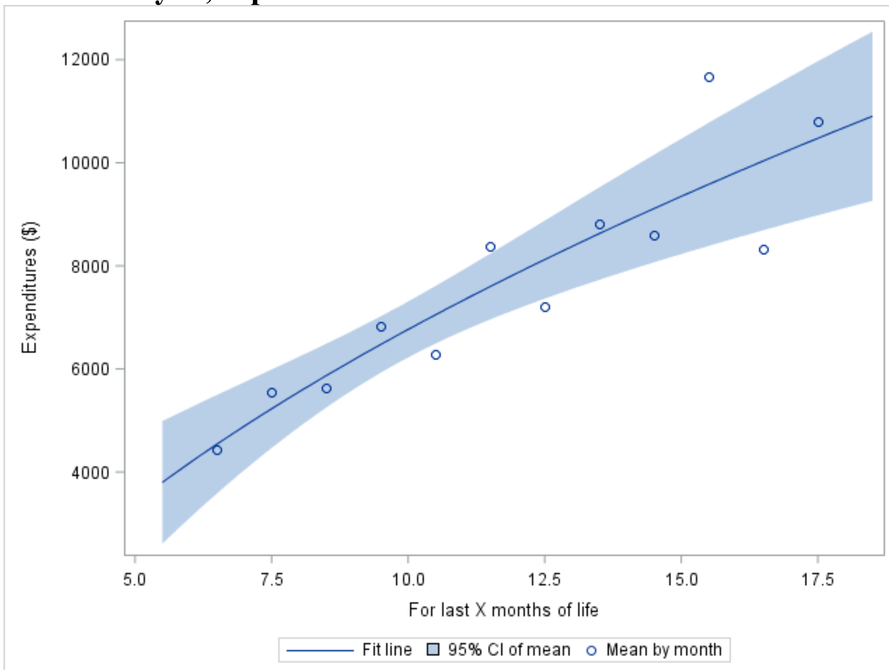


Figure 29. Regression curve for terminal year of life private insurance expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

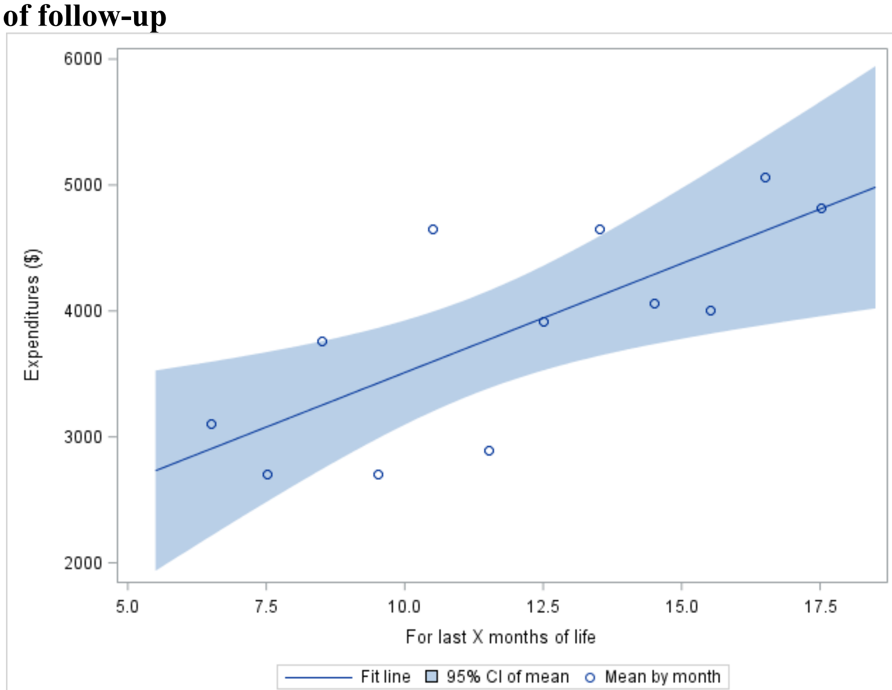


Figure 30. Regression curve for total terminal year of life <u>HMO</u> expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

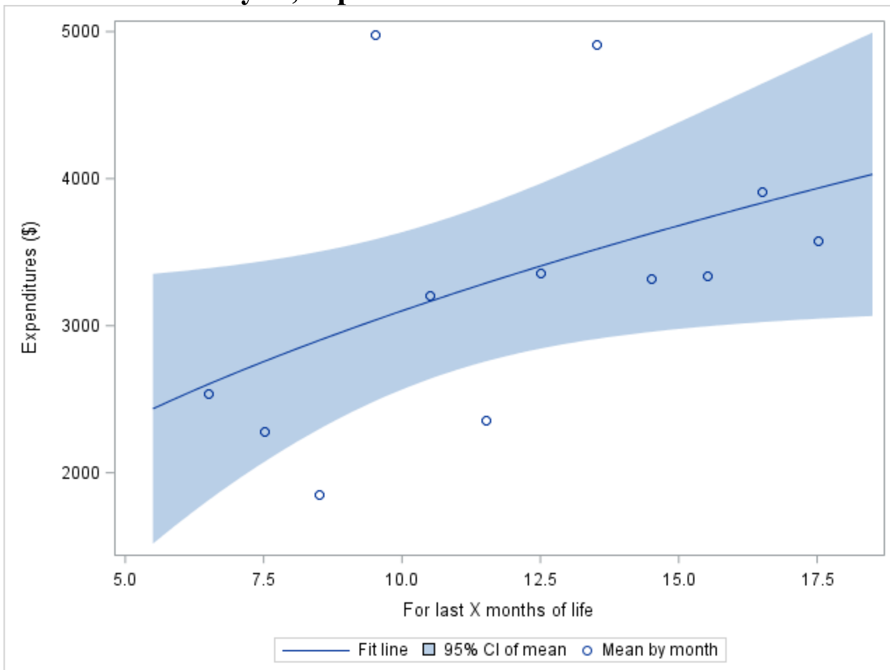


Figure 31. Regression curve for terminal year of life <u>dental</u> expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

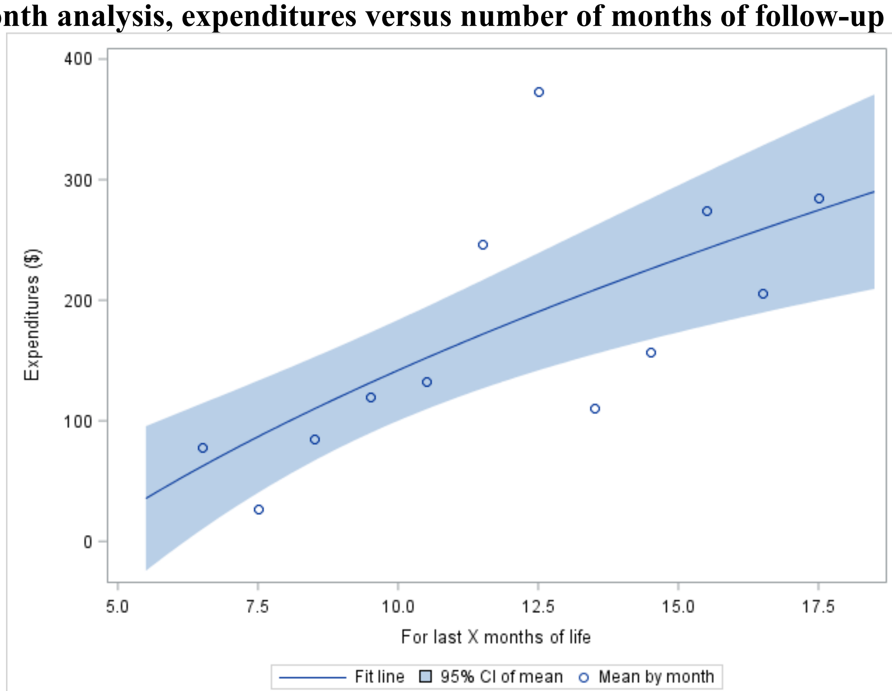


Figure 32. Regression curve for terminal year of life facility expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

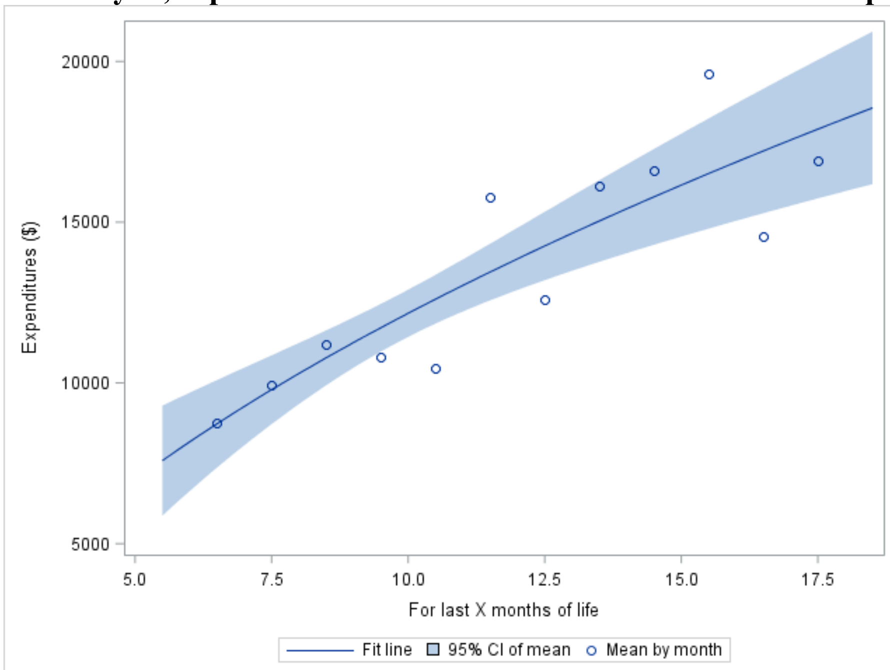


Figure 33. Regression curve for terminal year of life home health expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

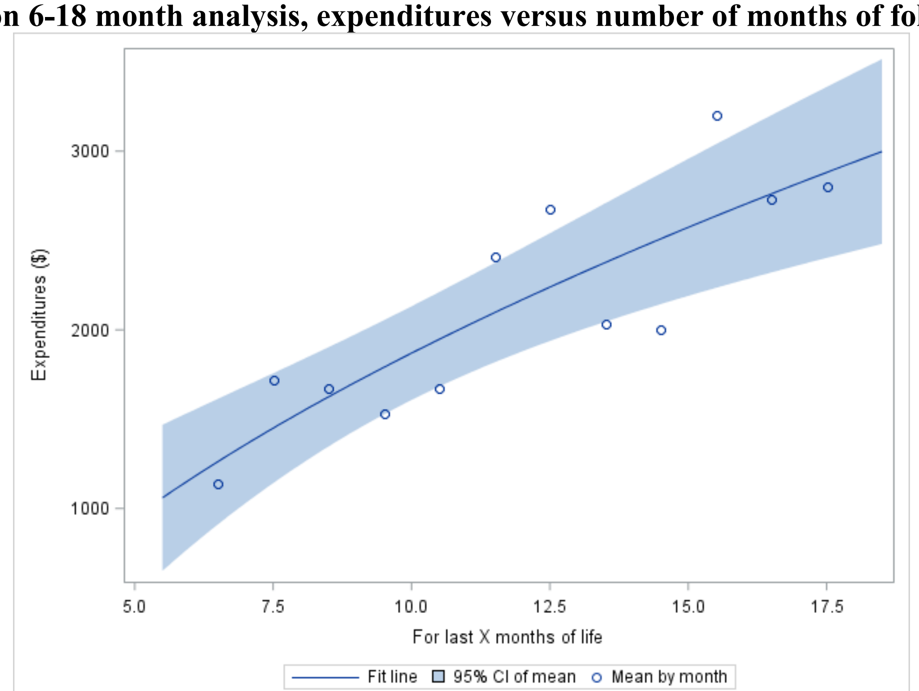


Figure 34. Regression curve for terminal year of life <u>hospice</u> expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

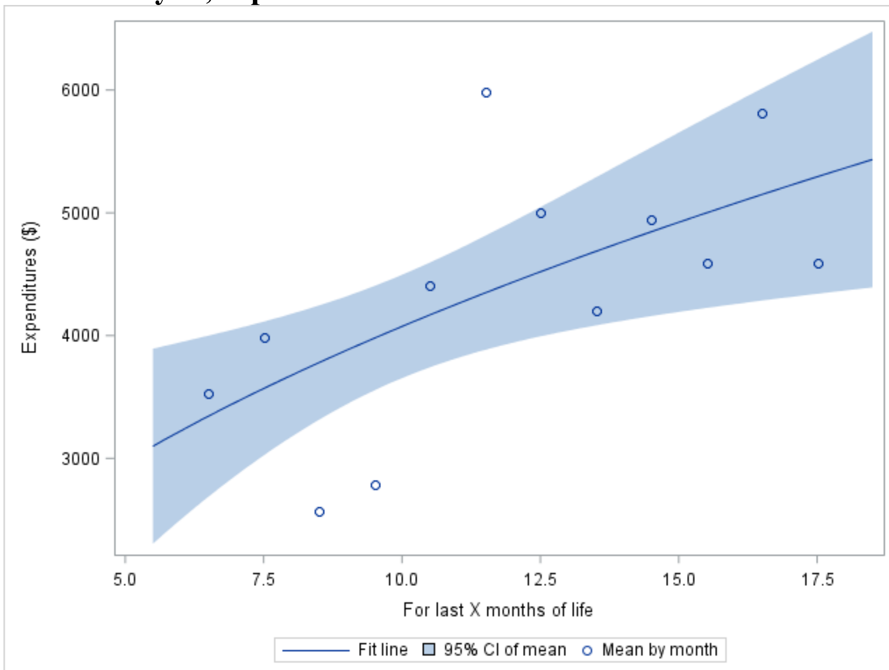


Figure 35. Regression curve for terminal year of life <u>inpatient hospital</u> expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

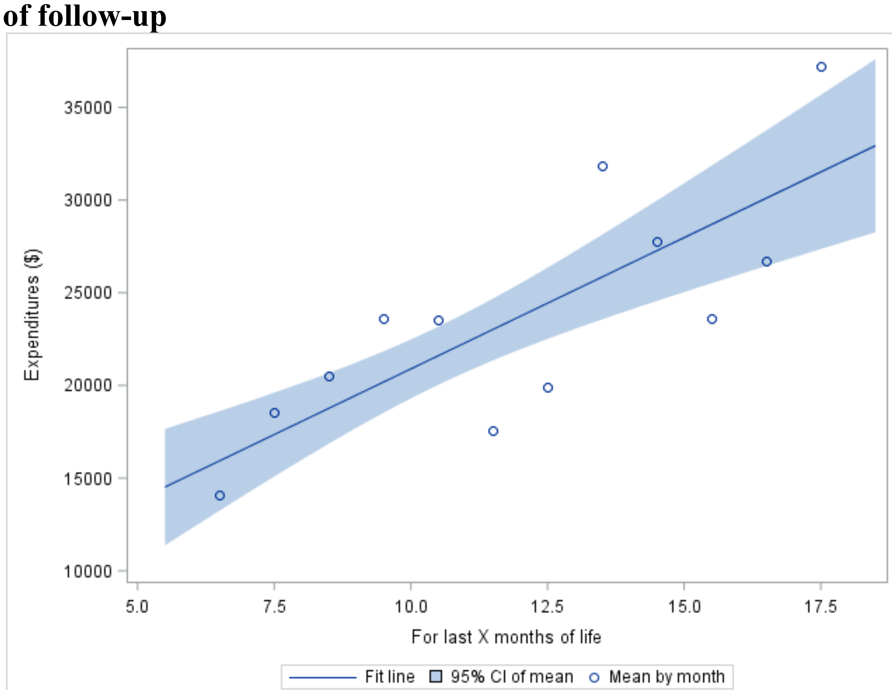


Figure 36. Regression curve for terminal year of life <u>institutional</u> expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

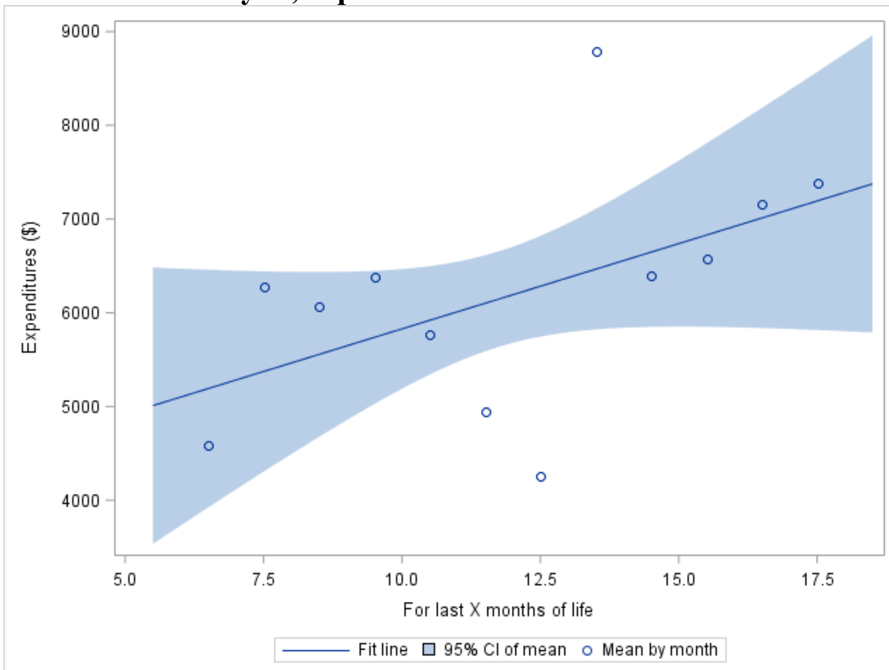


Figure 37. Regression curve for terminal year of life <u>medical provider</u> expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

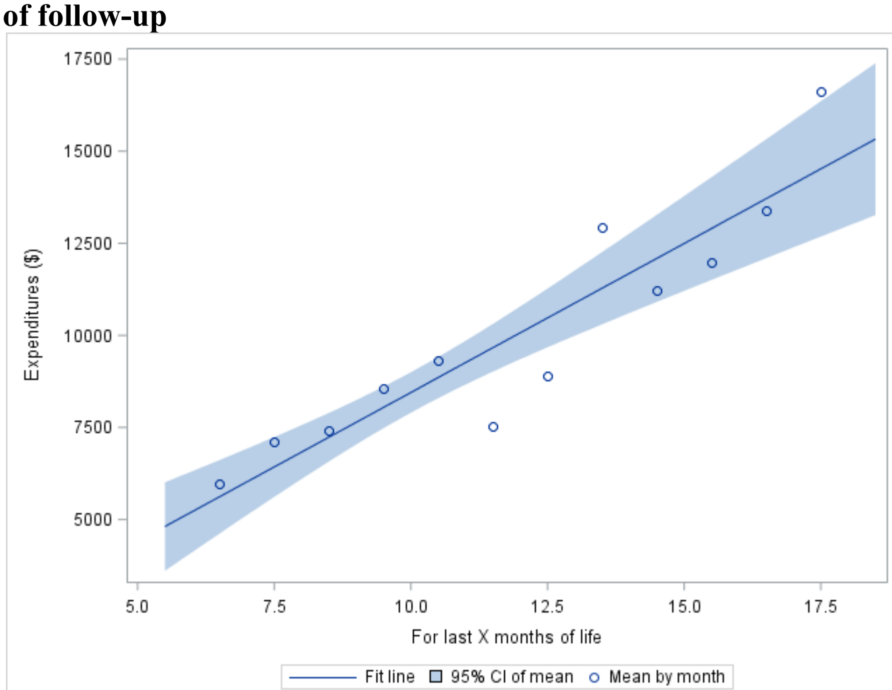


Figure 38. Regression curve for terminal year of life <u>outpatient hospital</u> expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up

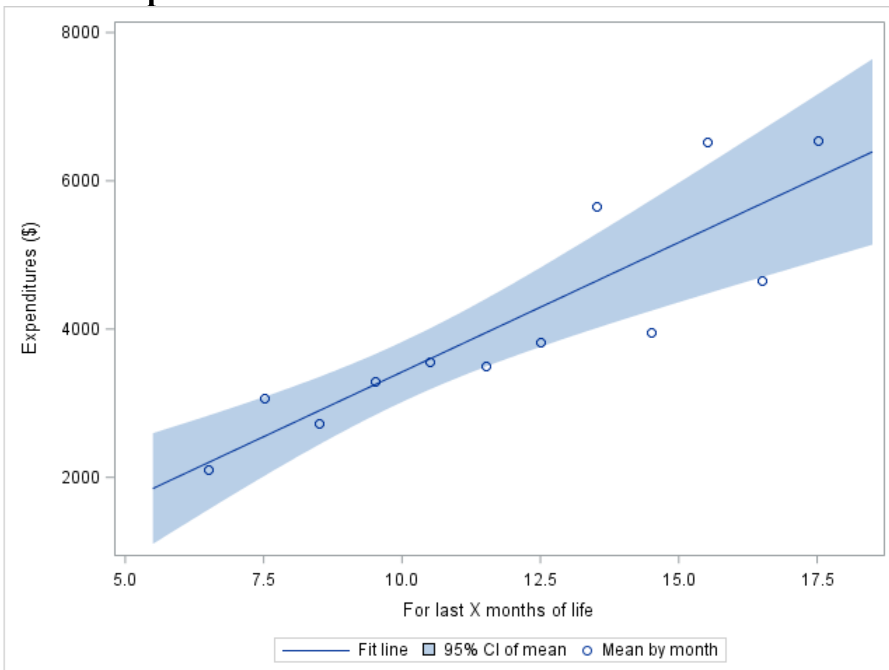
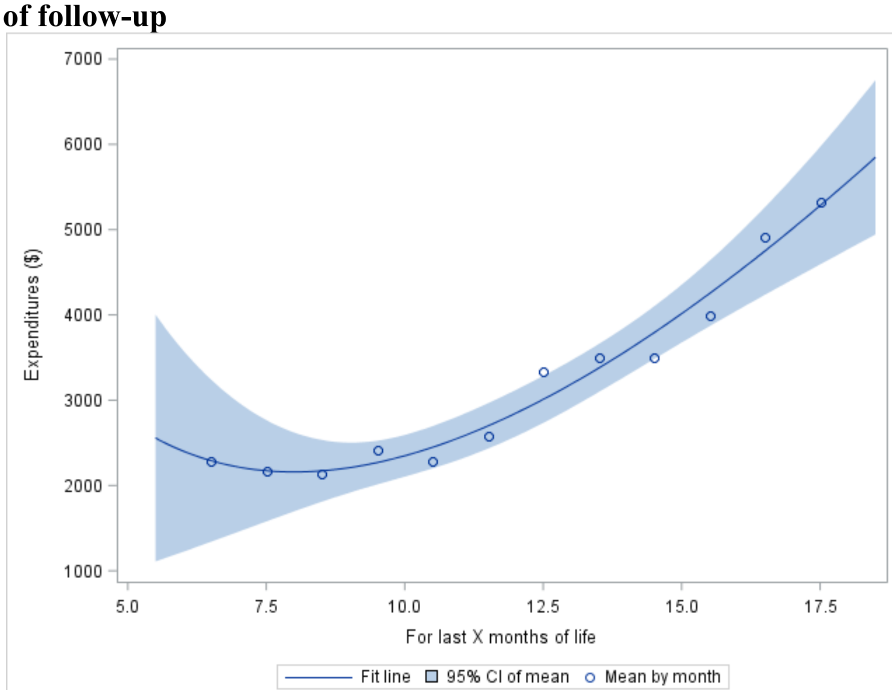


Figure 39. Regression curve for terminal year of life <u>prescribed medicine</u> expenditures based on 6-18 month analysis, expenditures versus number of months of follow-up



12.1.3 Graphs of superimposed regression curves for selected models in the 0-12 and 6-18 month analyses

Lines represent the fitted models; circles represent the averaged cumulative expenses for those with given months alive in calendar year of death. Shaded region about line represents pointwise 95% confidence band. Blue line and shaded region are for 0-12 month model. Red line and shaded region are for 6-18 month model.

Figure 40. Regression curves for <u>total</u> terminal year of life medical expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

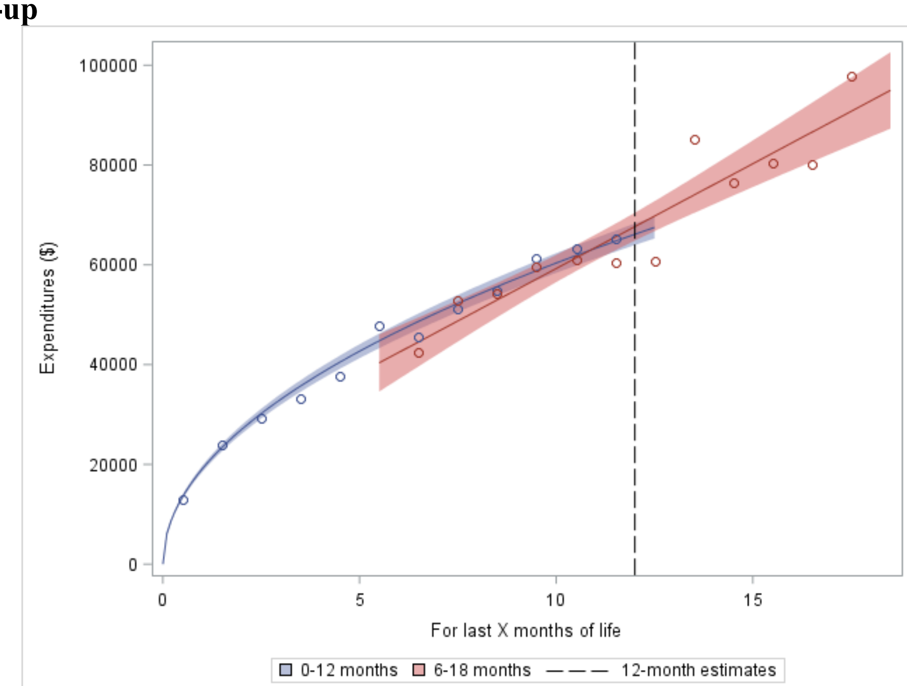


Figure 41. Regression curves for terminal year of life <u>Medicare</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

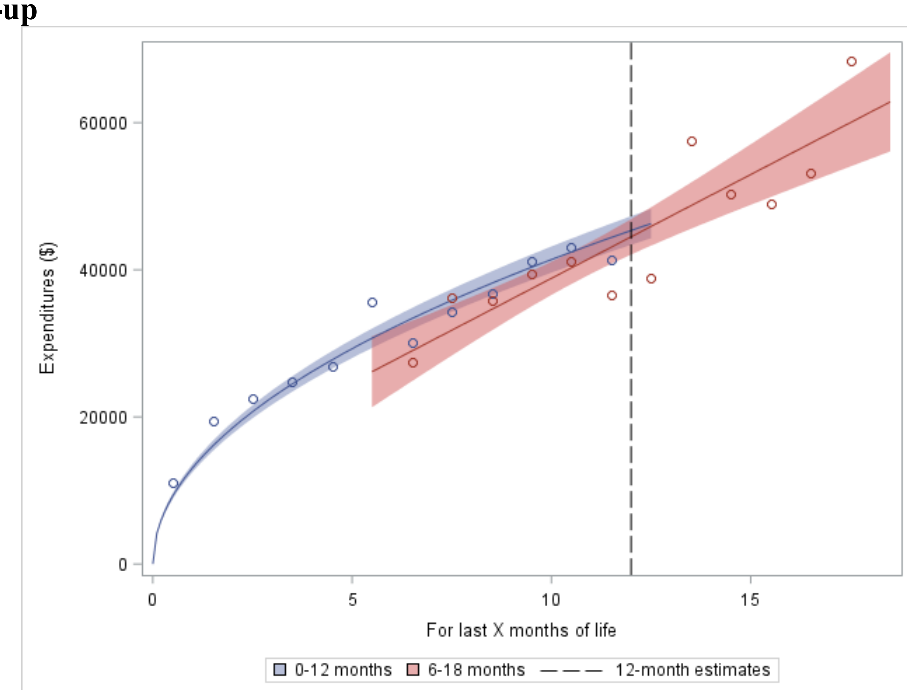


Figure 42. Regression curves for terminal year of life <u>non-Medicare</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

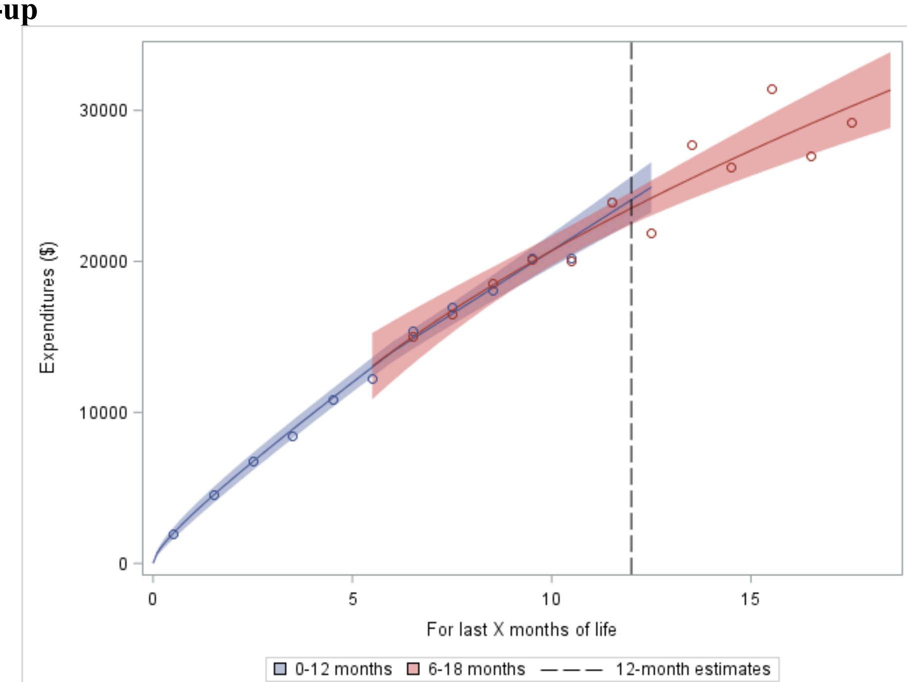


Figure 43. Regression curves for total terminal year of life <u>private</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

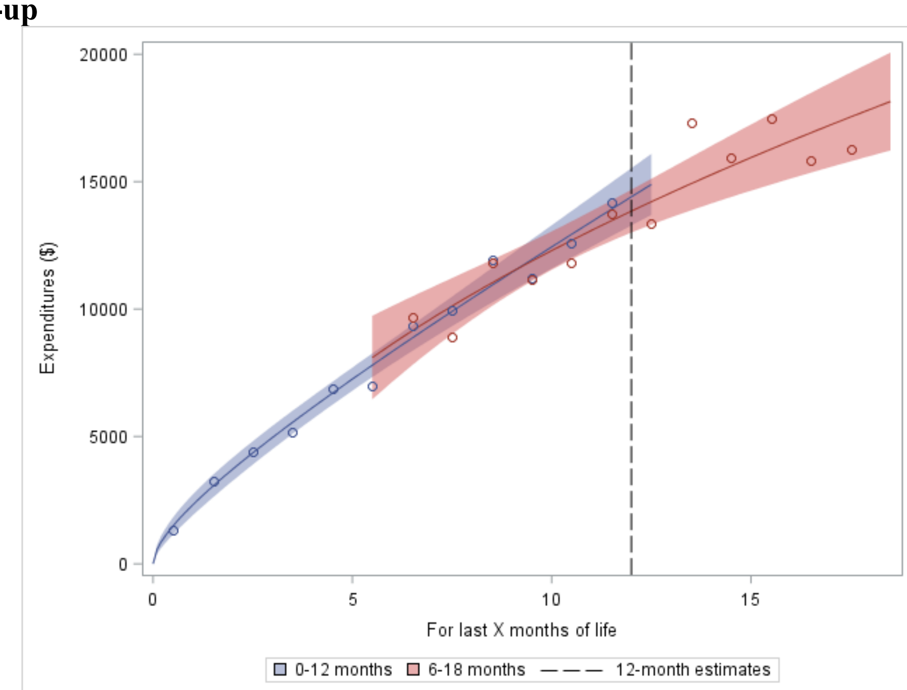


Figure 44. Regression curves for total terminal year of life <u>public</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

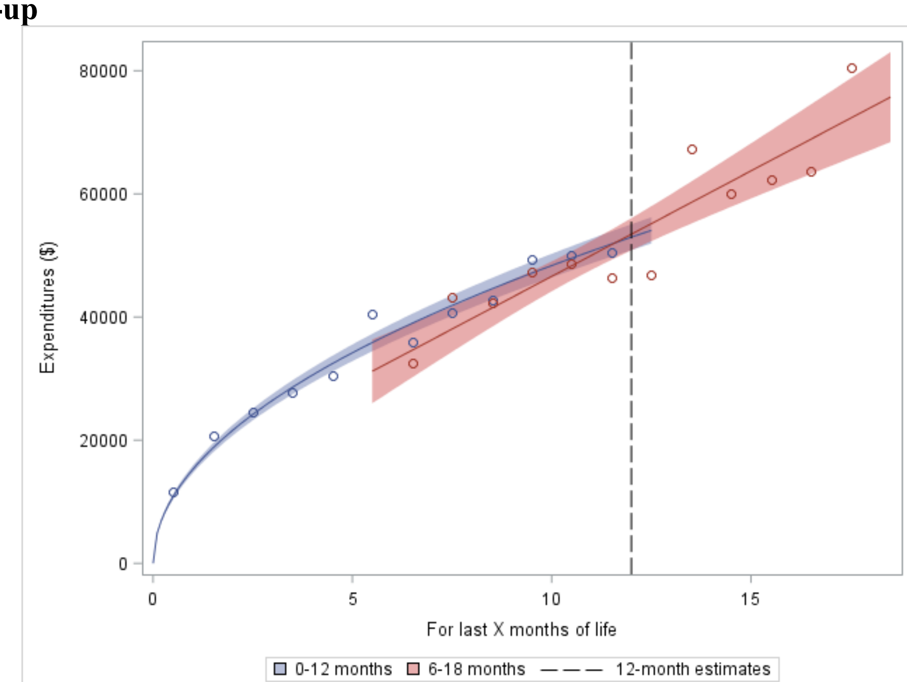


Figure 45. Regression curves for terminal year of life out-of-pocket expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

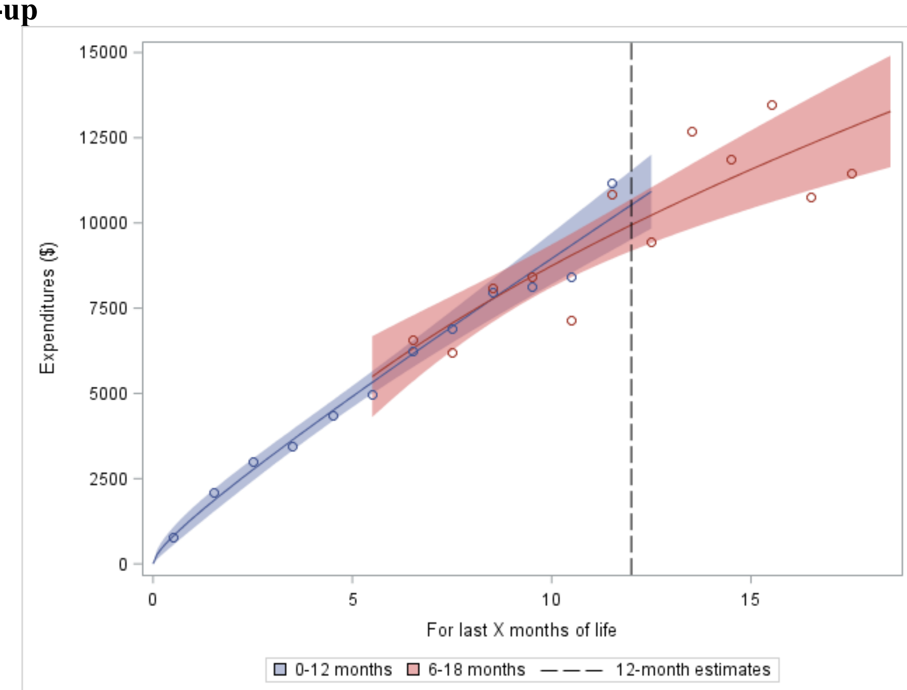


Figure 46. Regression curves for terminal year of life Medicaid expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

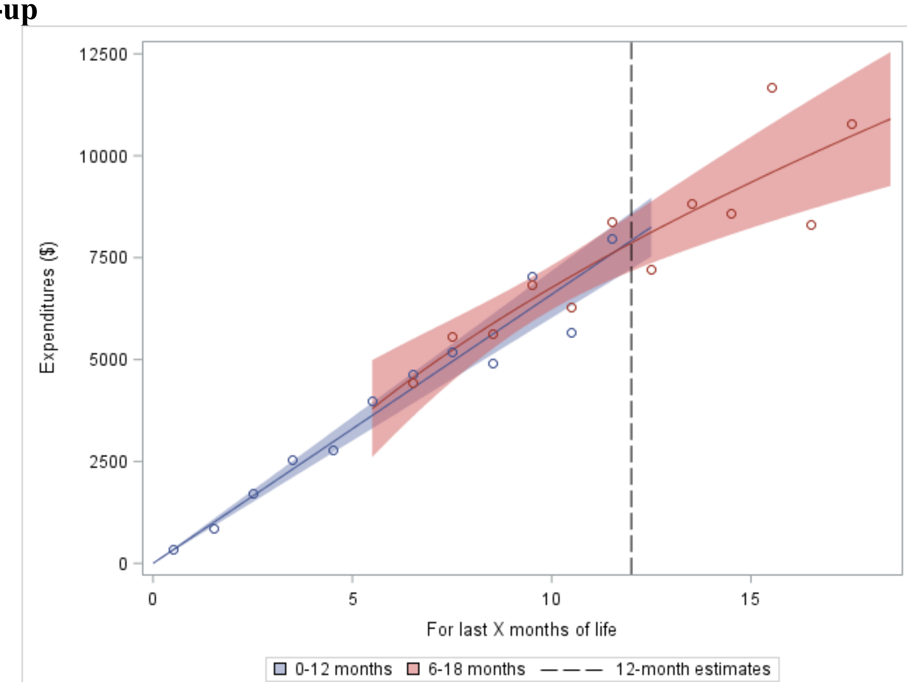


Figure 47. Regression curves for terminal year of life <u>private insurance</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

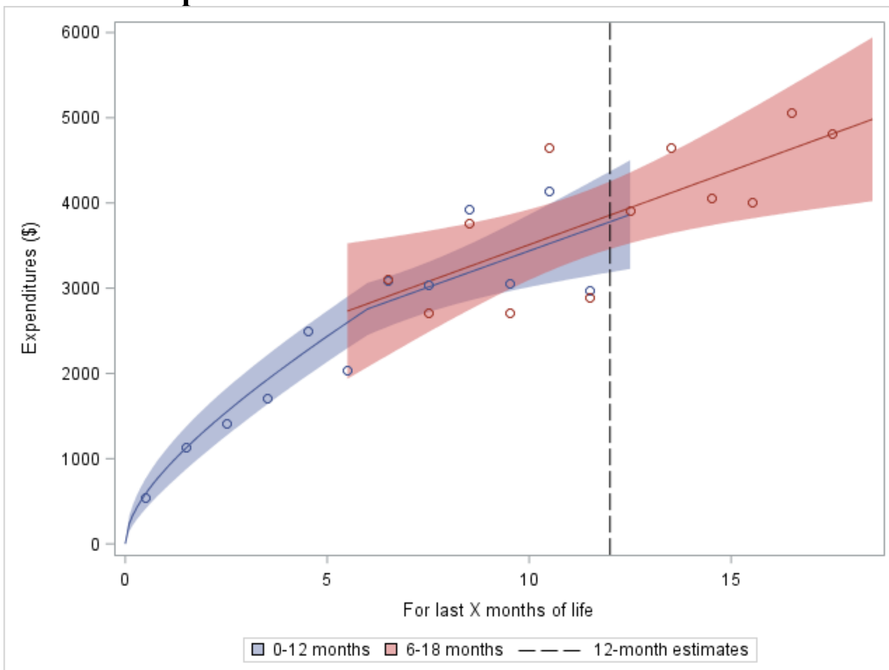


Figure 48. Regression curves for total terminal year of life <u>HMO</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

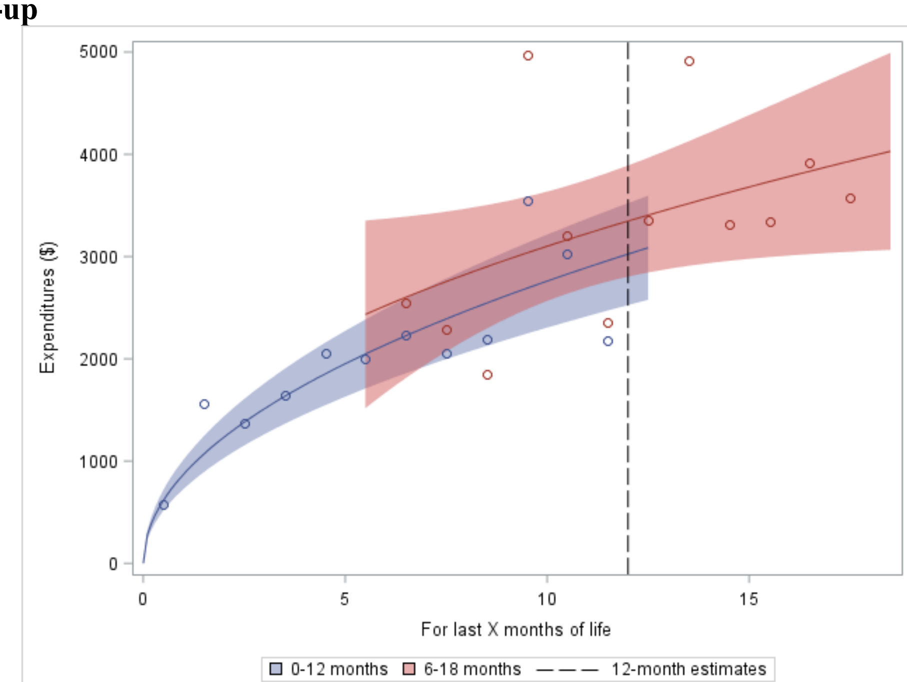


Figure 49. Regression curves for terminal year of life dental expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

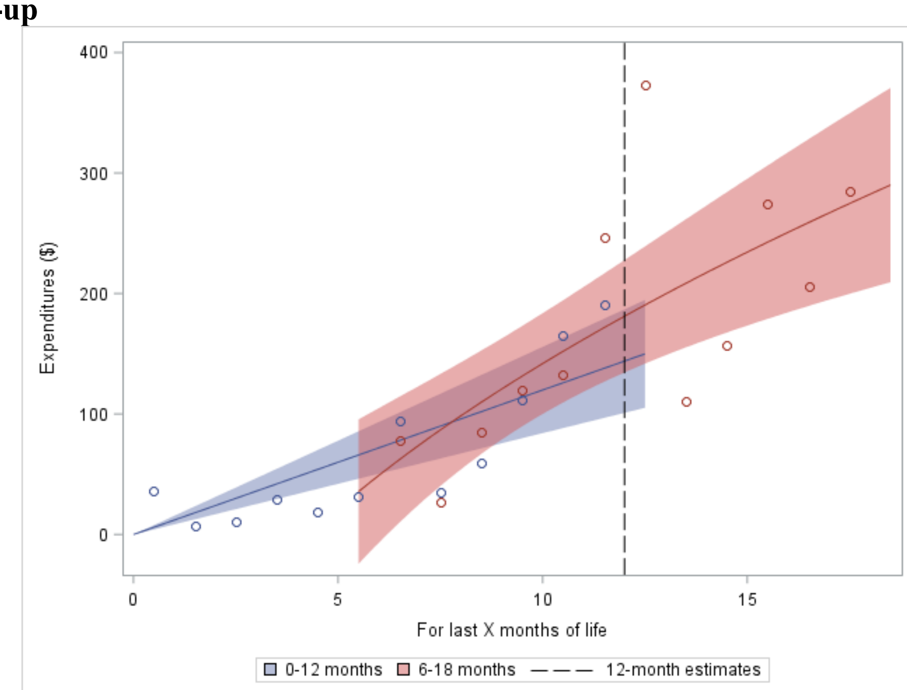


Figure 50. Regression curves for terminal year of life facility expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

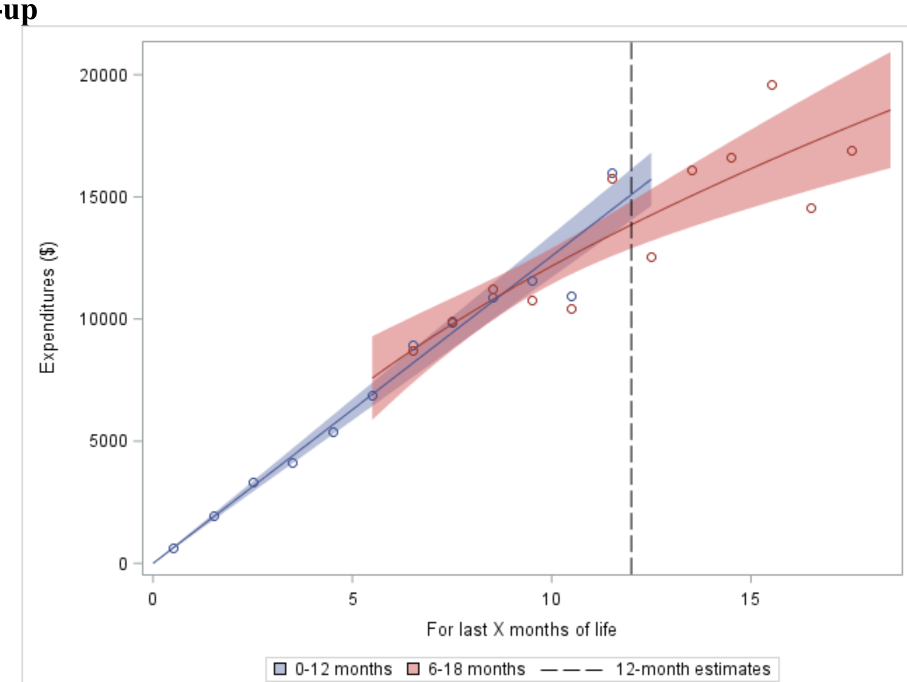


Figure 51. Regression curves for terminal year of life <u>home health</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

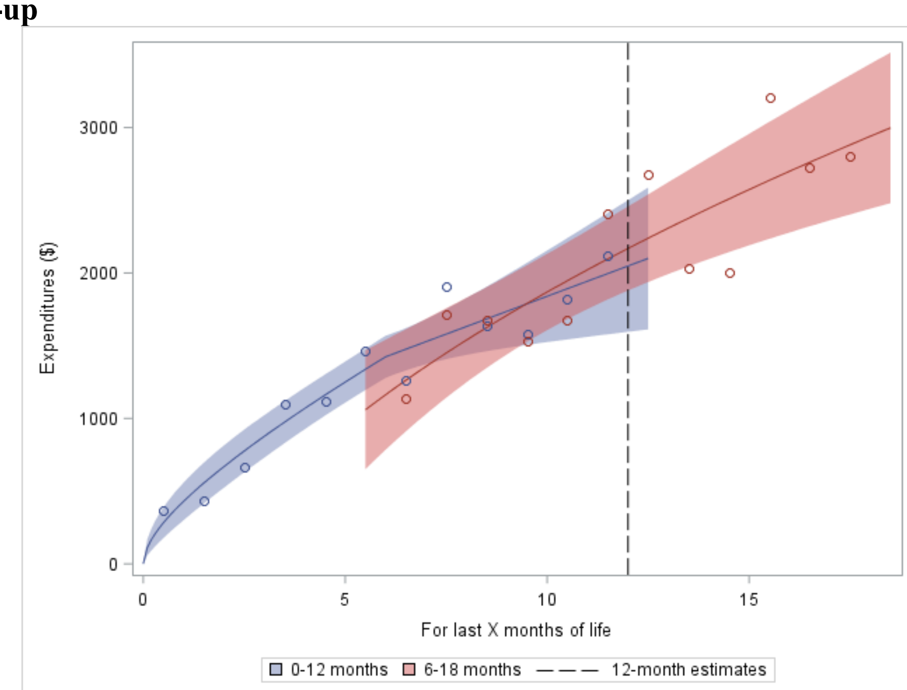


Figure 52. Regression curves for terminal year of life <u>hospice</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

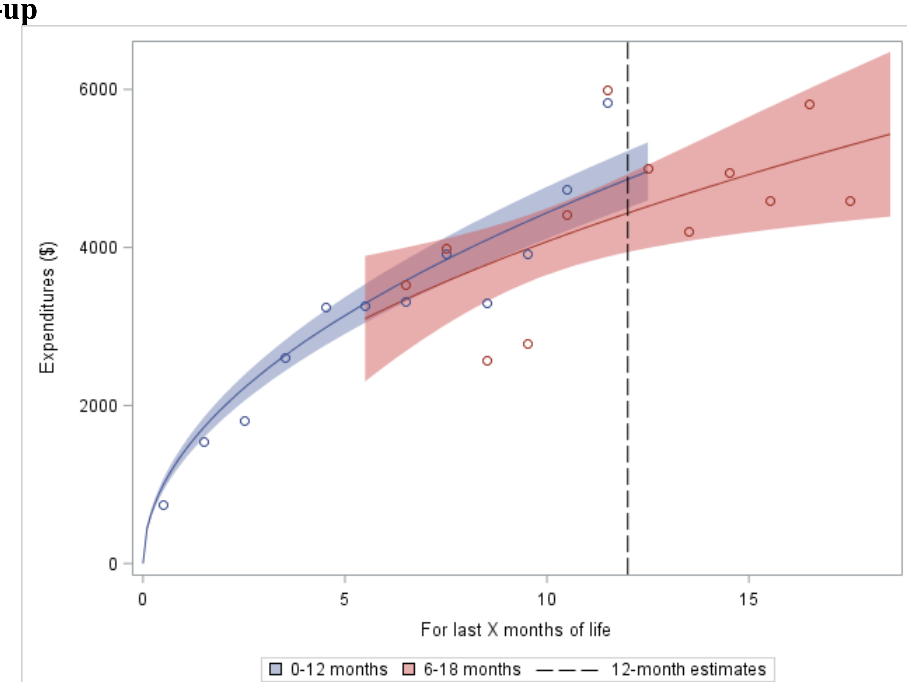


Figure 53. Regression curves for terminal year of life <u>inpatient hospital</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

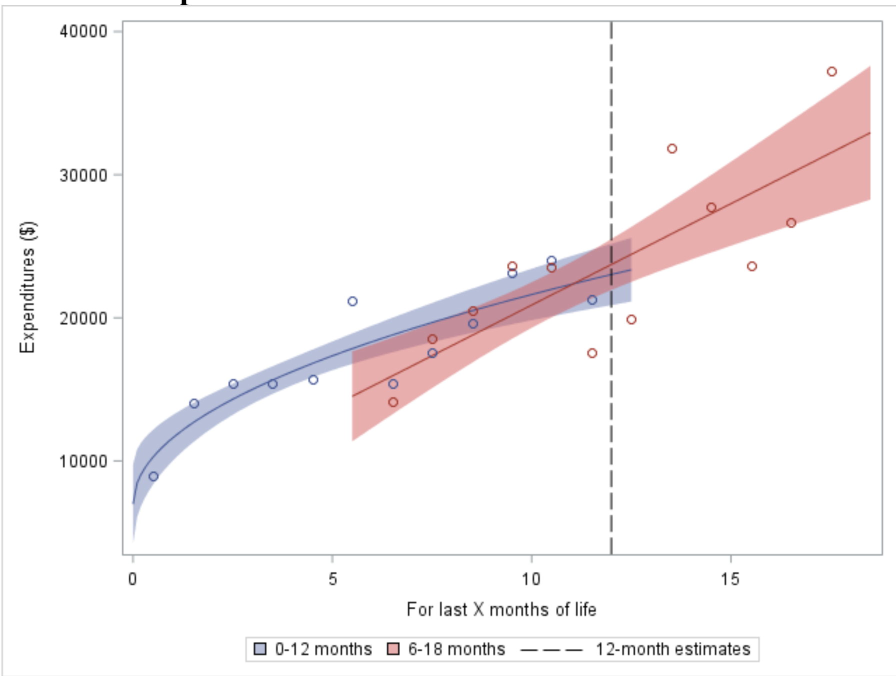


Figure 54. Regression curves for terminal year of life <u>institutional</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

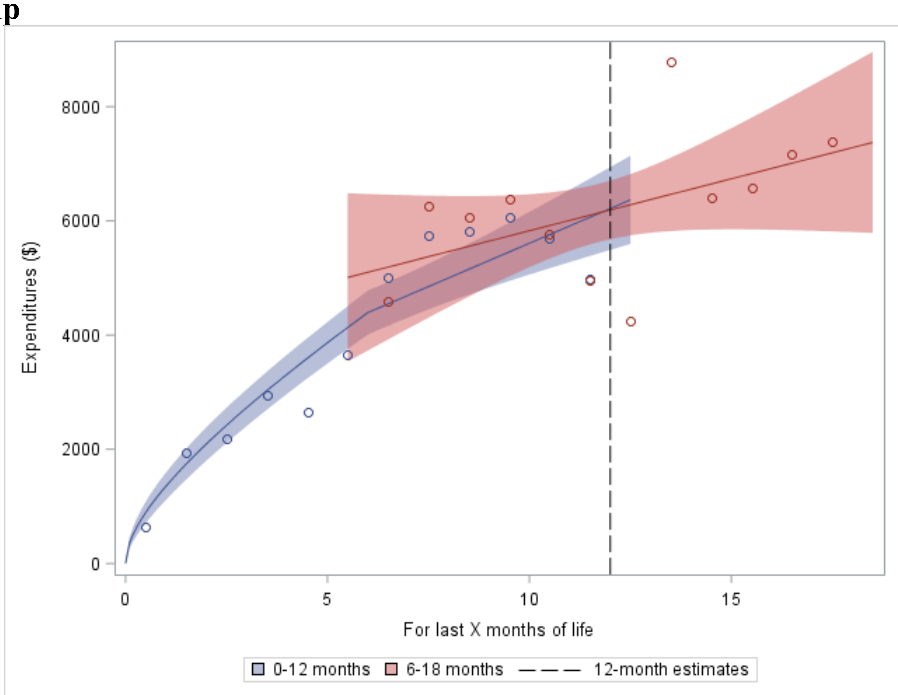


Figure 55. Regression curves for terminal year of life medical provider expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

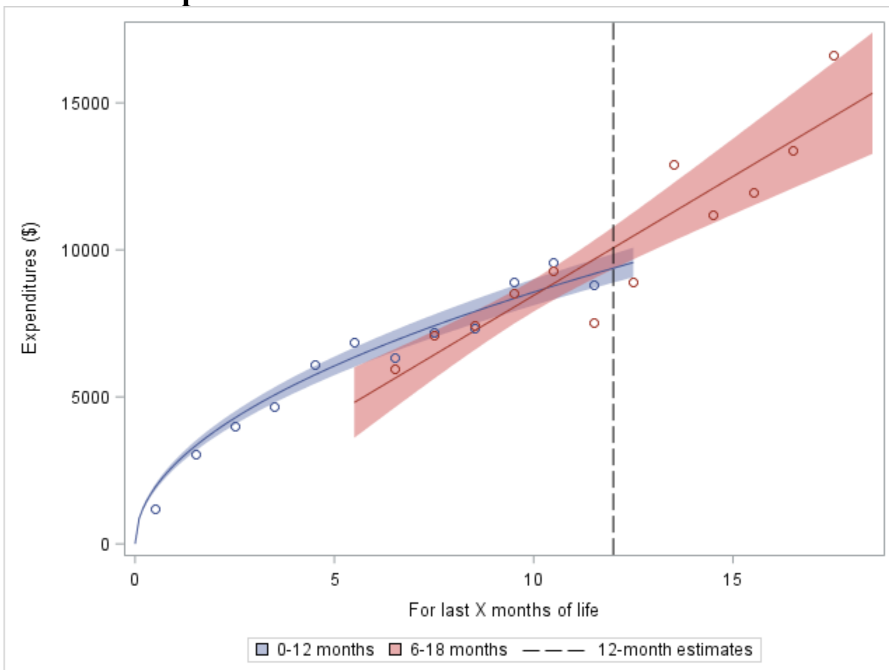


Figure 56. Regression curves for terminal year of life outpatient hospital expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up

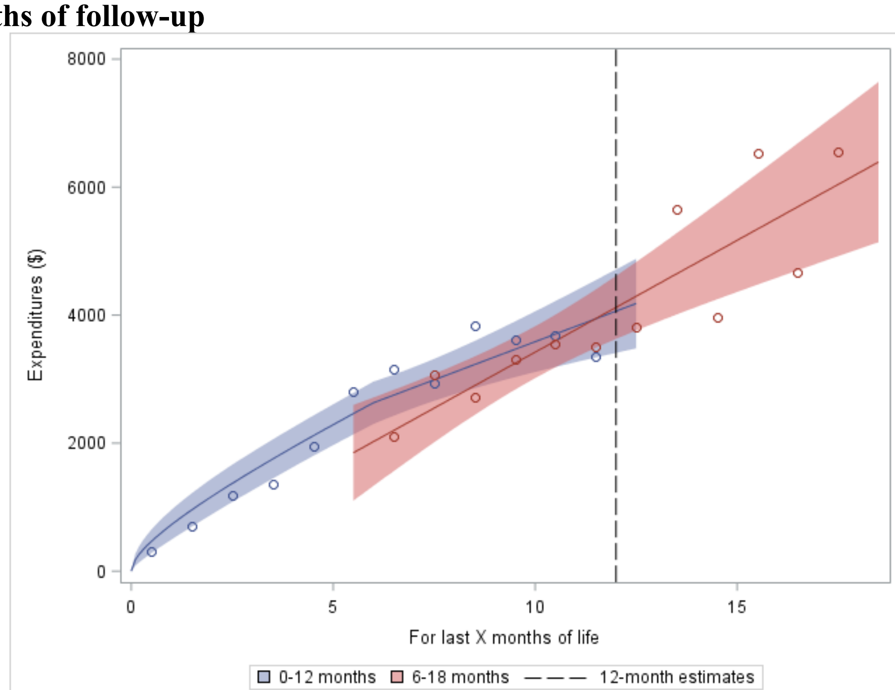
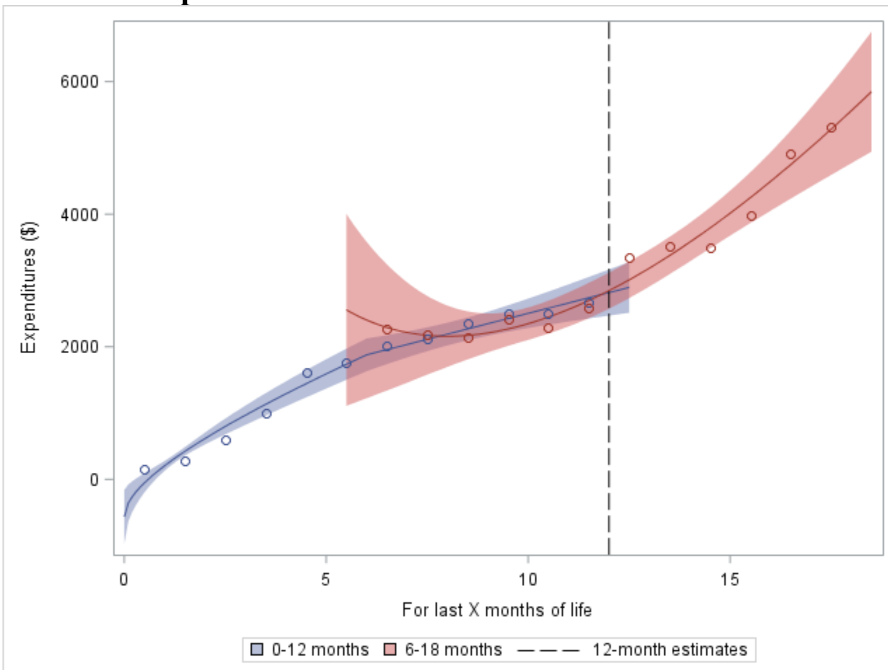


Figure 57. Regression curves for terminal year of life <u>prescribed medicine</u> expenditures based on 0-12 and 6-18 month analyses, expenditures versus number of months of follow-up



12.2 Sensitivity analyses

12.2.1 Graphs of superimposed regression curves for selected models comparing given date of death versus midpoint of death month

Lines represent the fitted models; circles represent the averaged cumulative expenses for those with given months alive in calendar year of death. Shaded region about line represents pointwise 95% confidence band. Blue line and shaded region are for the model using the given date of death. Red line and shaded region are for the model using the midpoint of the month of death.

Figure 58. Regression curves for <u>total</u> terminal year of life medical expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

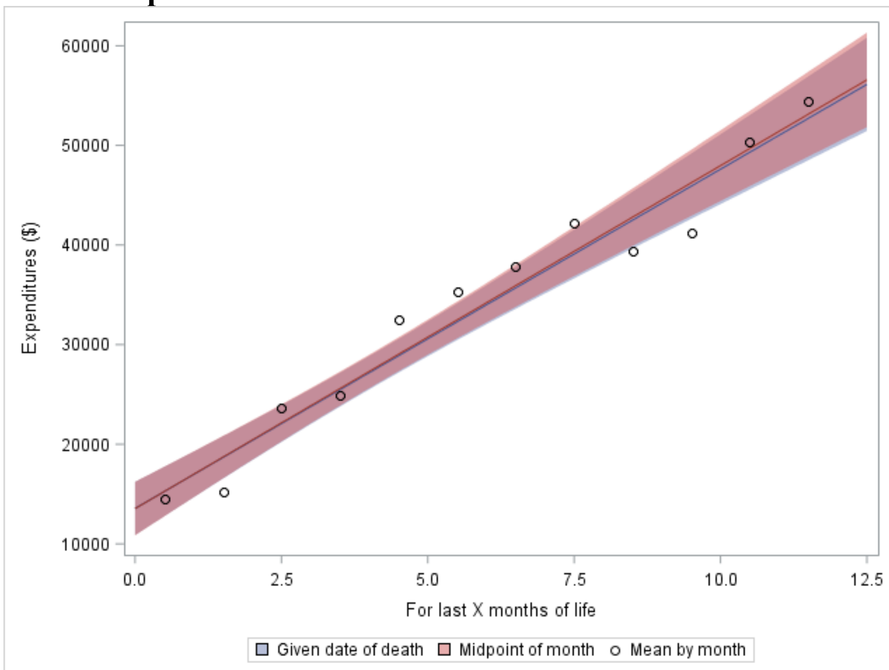


Figure 59. Regression curves for terminal year of life <u>Medicare</u> expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

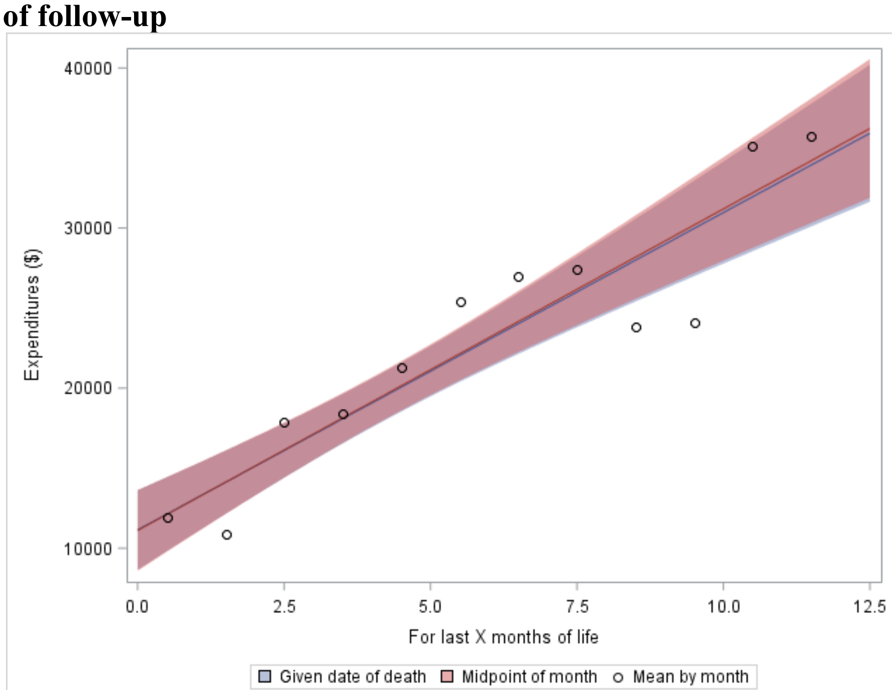


Figure 60. Regression curves for terminal year of life <u>non-Medicare</u> expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

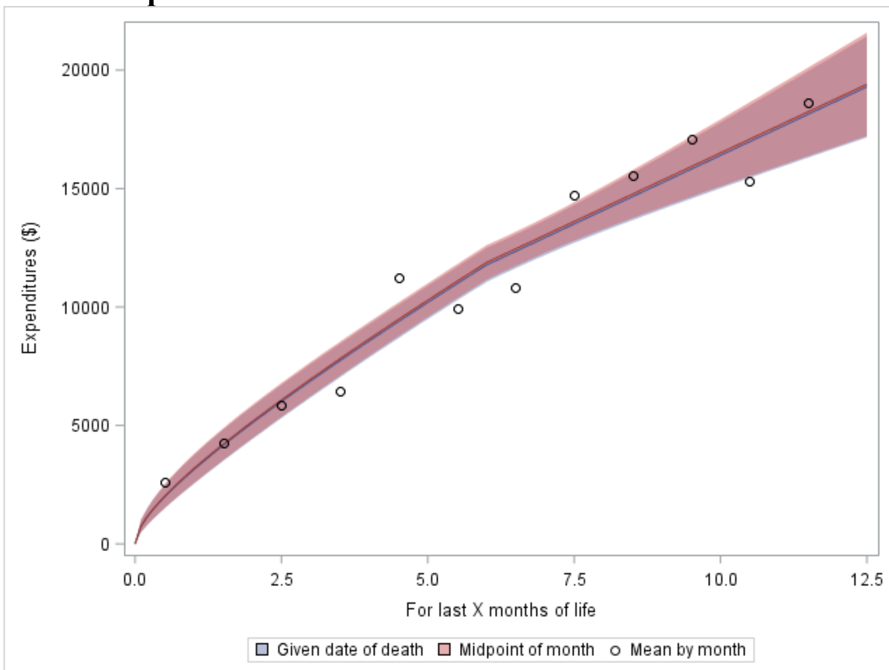


Figure 61. Regression curves for total terminal year of life <u>private</u> expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

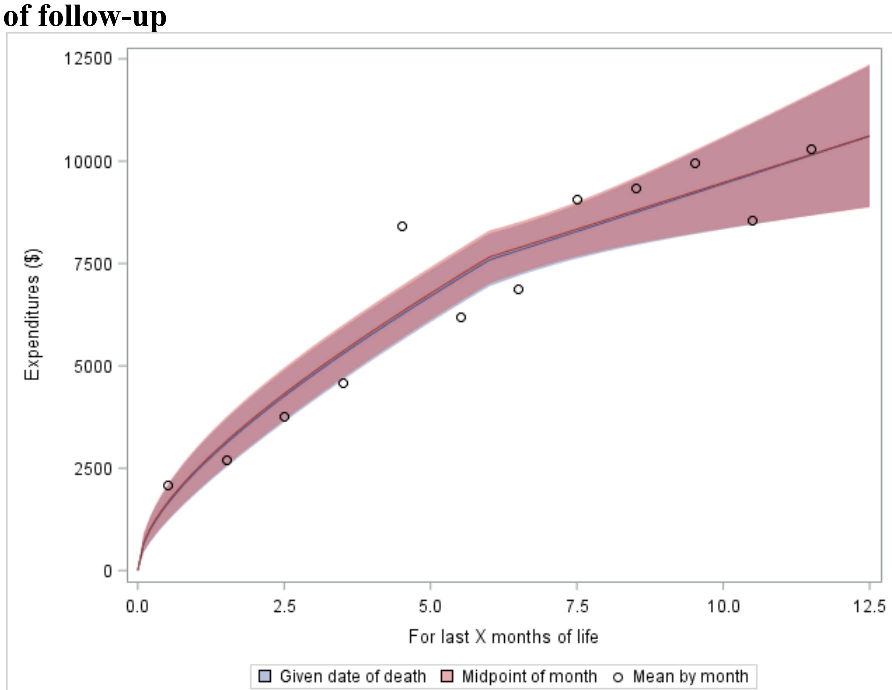


Figure 62. Regression curves for total terminal year of life public expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

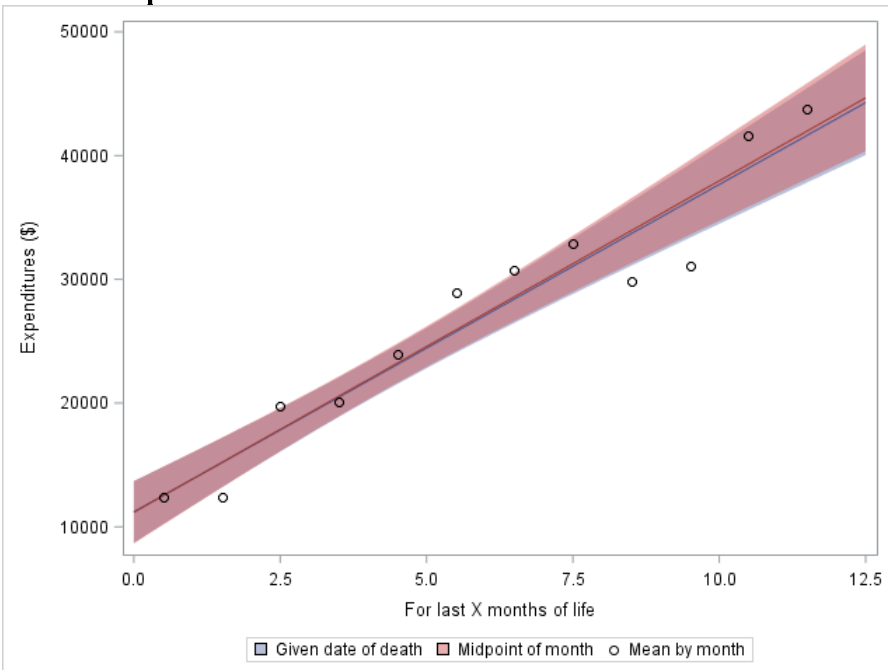


Figure 63. Regression curves for terminal year of life out-of-pocket expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

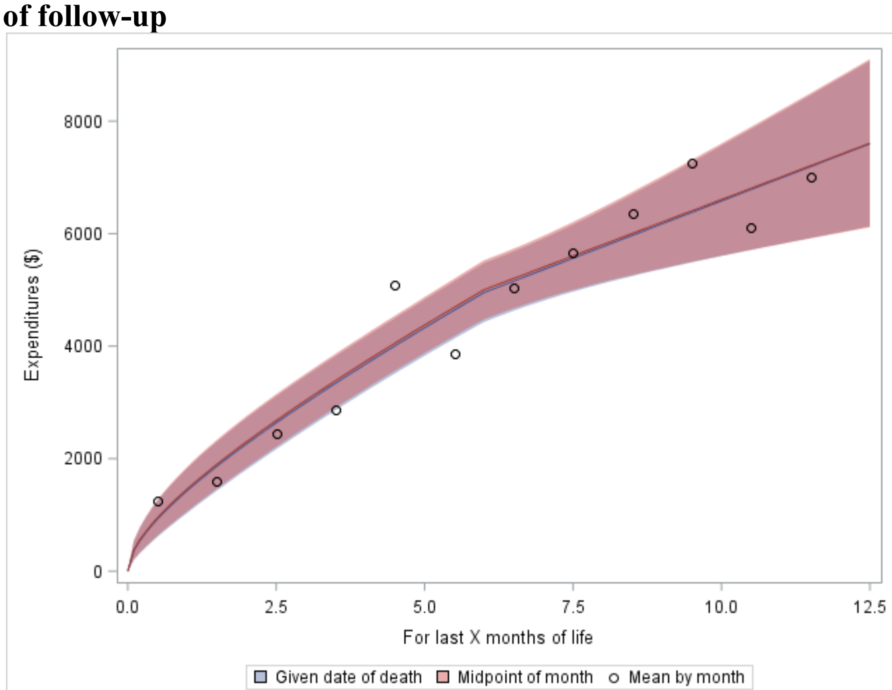


Figure 64. Regression curves for terminal year of life Medicaid expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

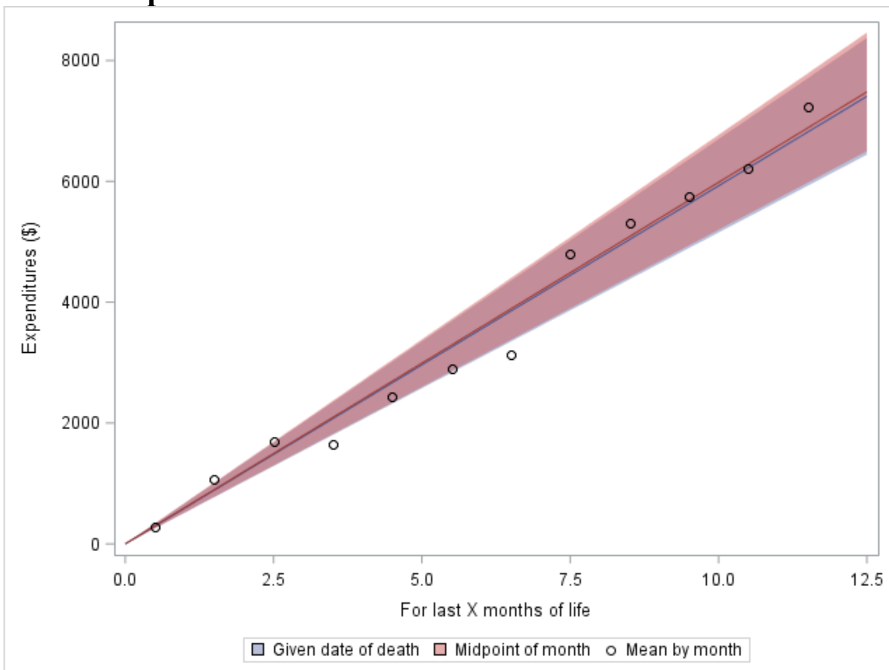


Figure 65. Regression curves for terminal year of life private insurance expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

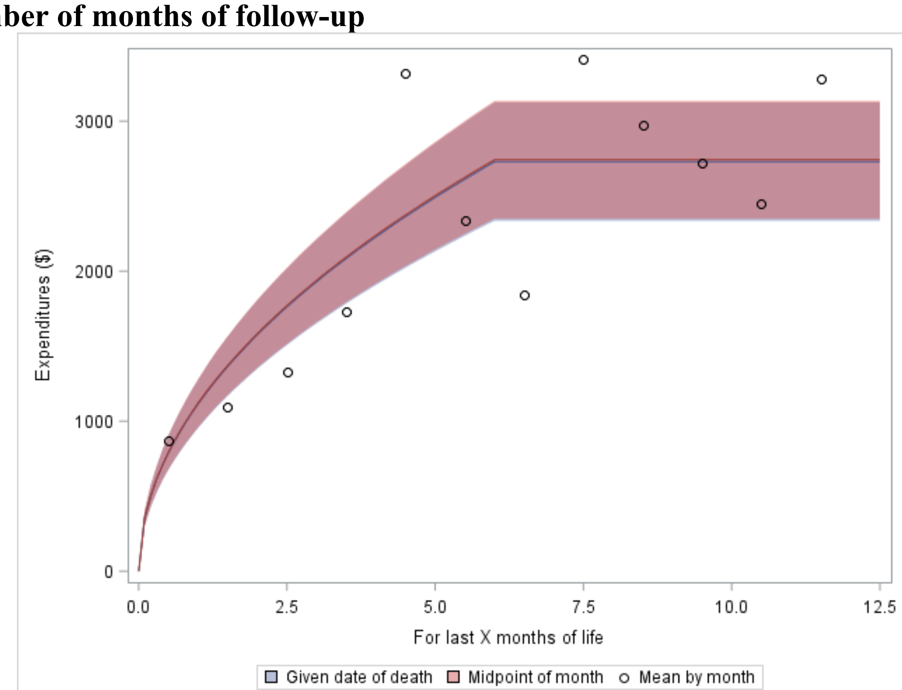


Figure 66. Regression curves for total terminal year of life <u>HMO</u> expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

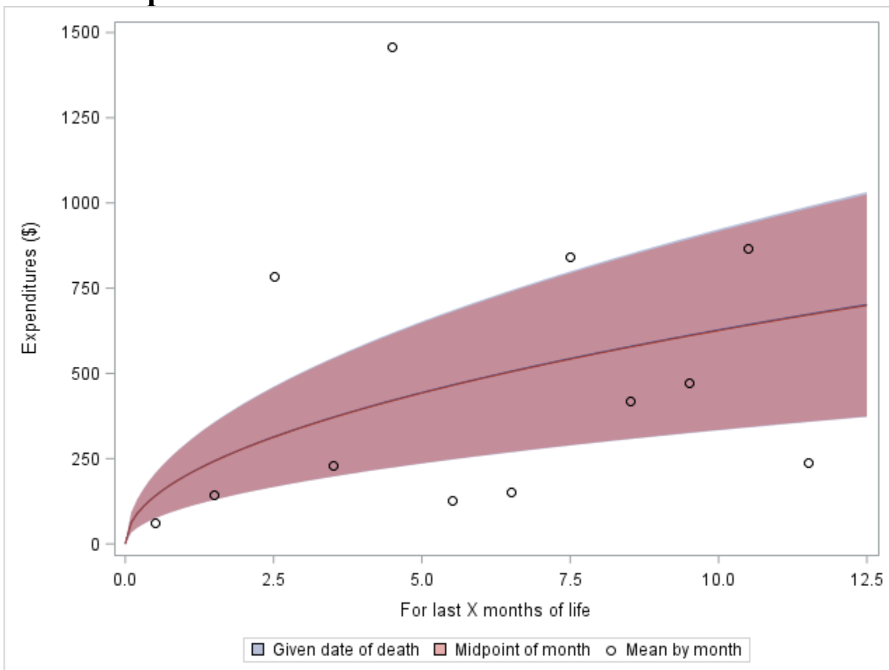


Figure 67. Regression curves for terminal year of life <u>dental</u> expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

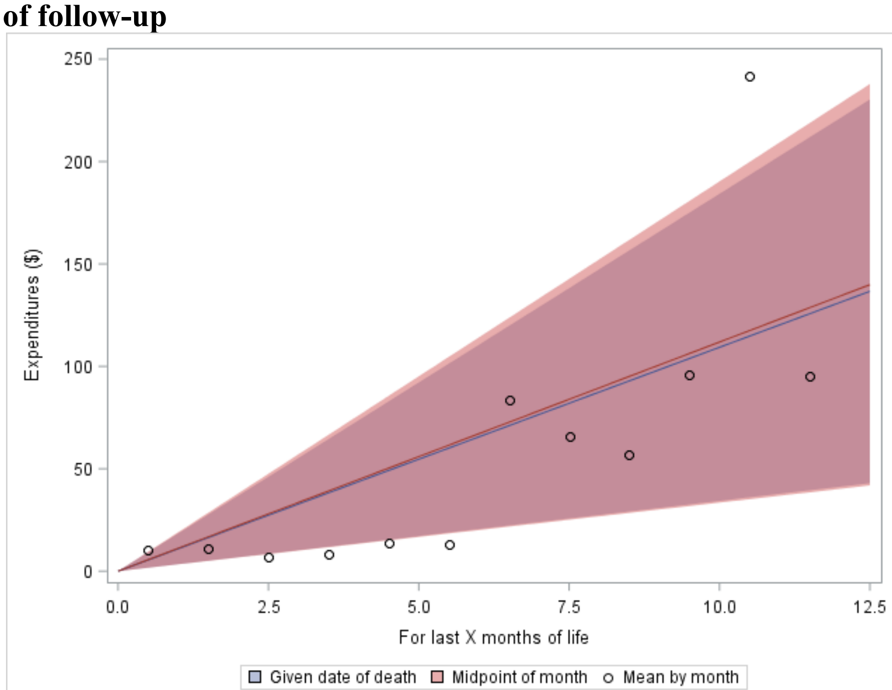


Figure 68. Regression curves for terminal year of life facility expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

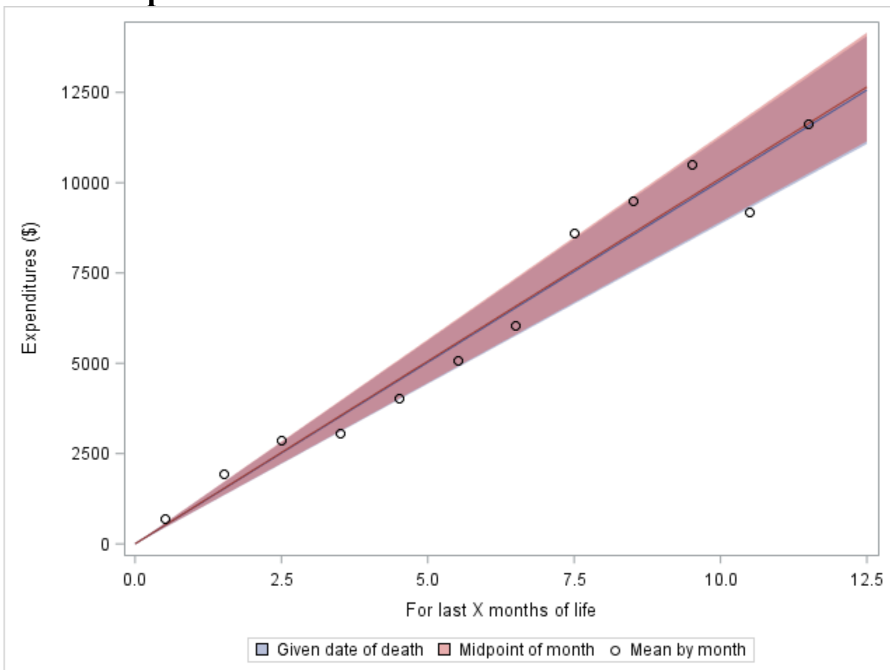


Figure 69. Regression curves for terminal year of life home health expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

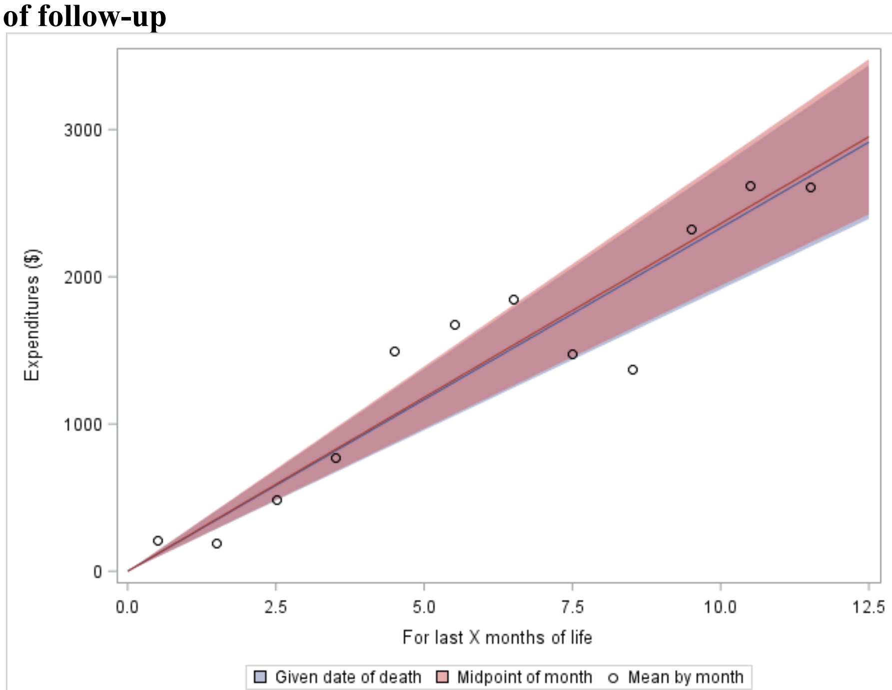


Figure 70. Regression curves for terminal year of life <u>hospice</u> expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

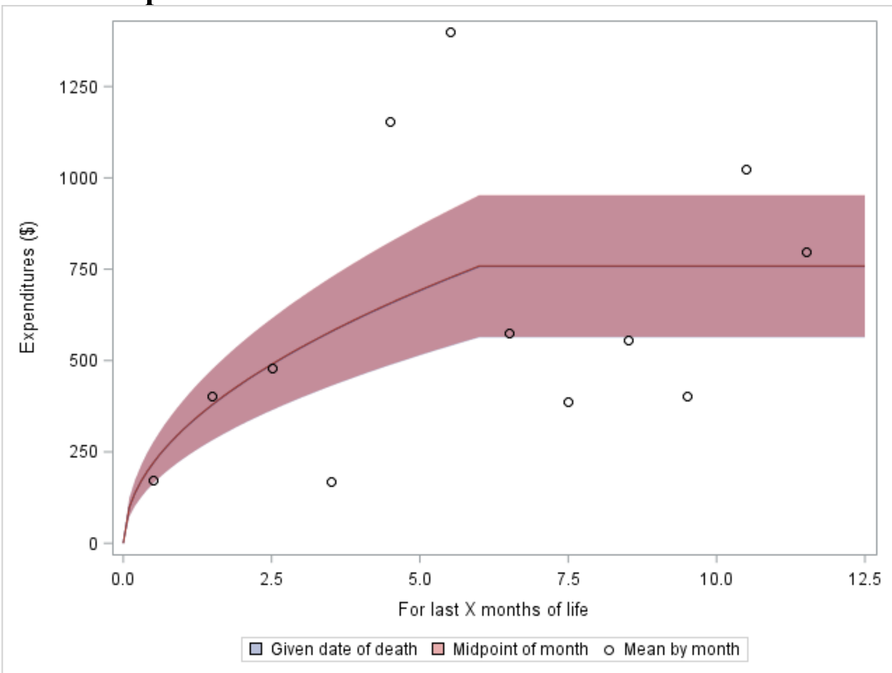


Figure 71. Regression curves for terminal year of life <u>inpatient hospital</u> expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

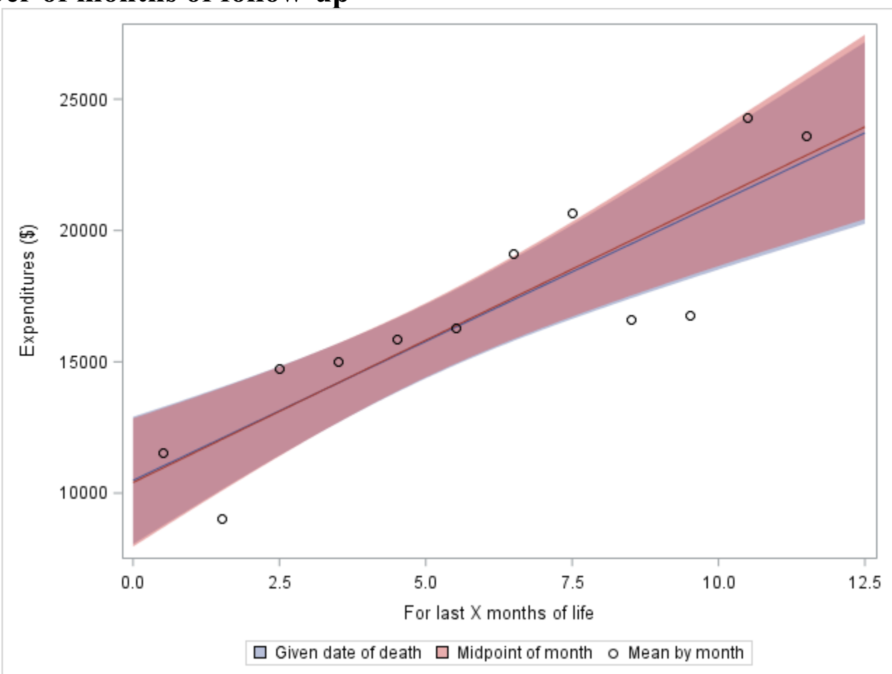


Figure 72. Regression curves for terminal year of life institutional expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

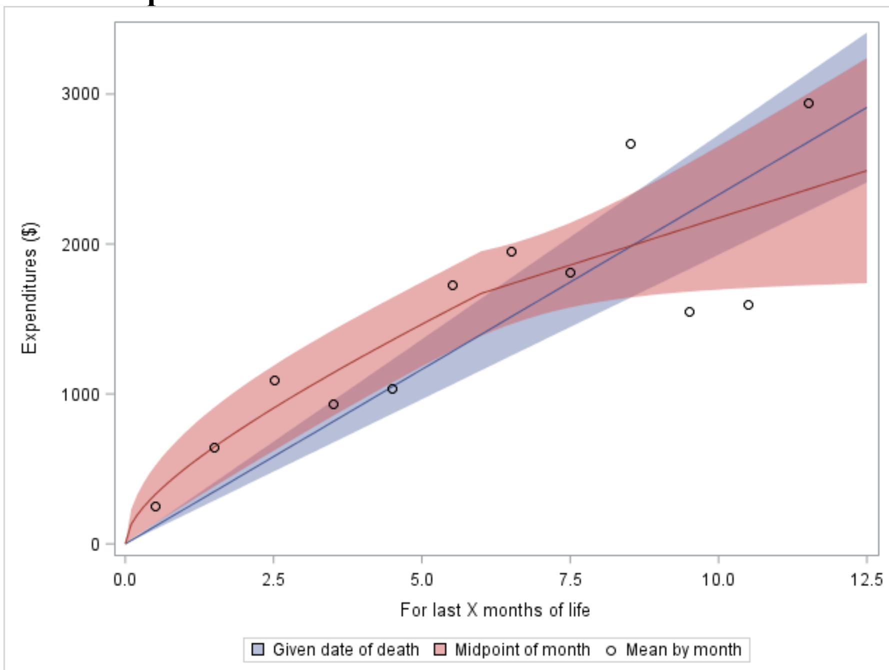


Figure 73. Regression curves for terminal year of life institutional expenditures based on given date of death model, expenditures vs number of months of follow-up

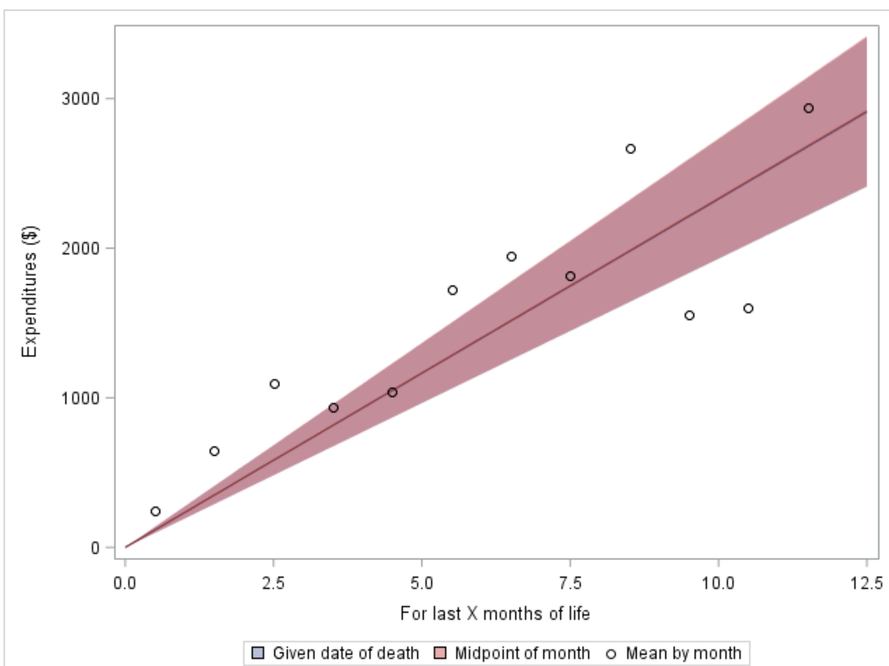


Figure 74. Regression curves for terminal year of life institutional expenditures based on midpoint of month model, expenditures vs number of months of follow-up

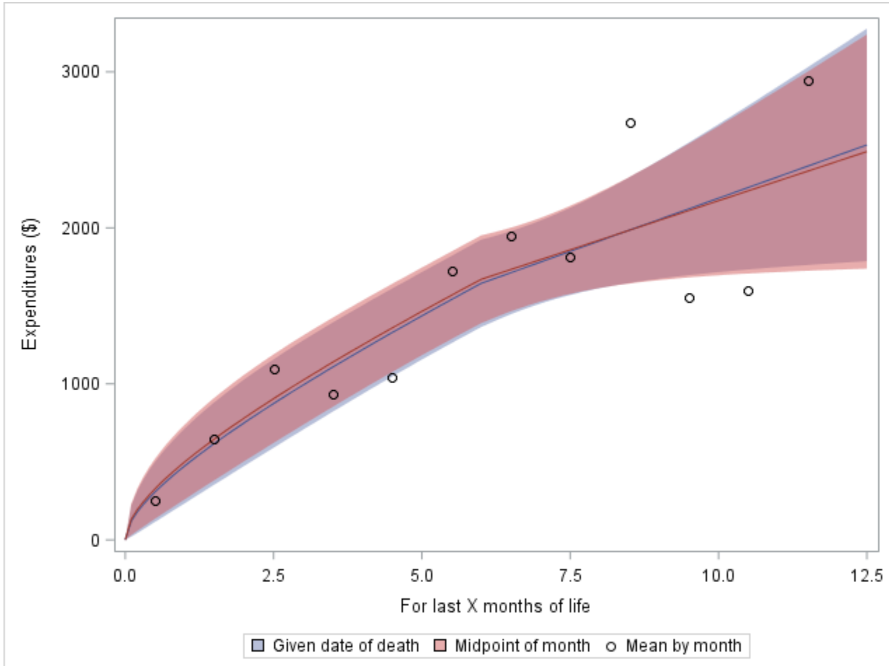


Figure 75. Regression curves for terminal year of life medical provider expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

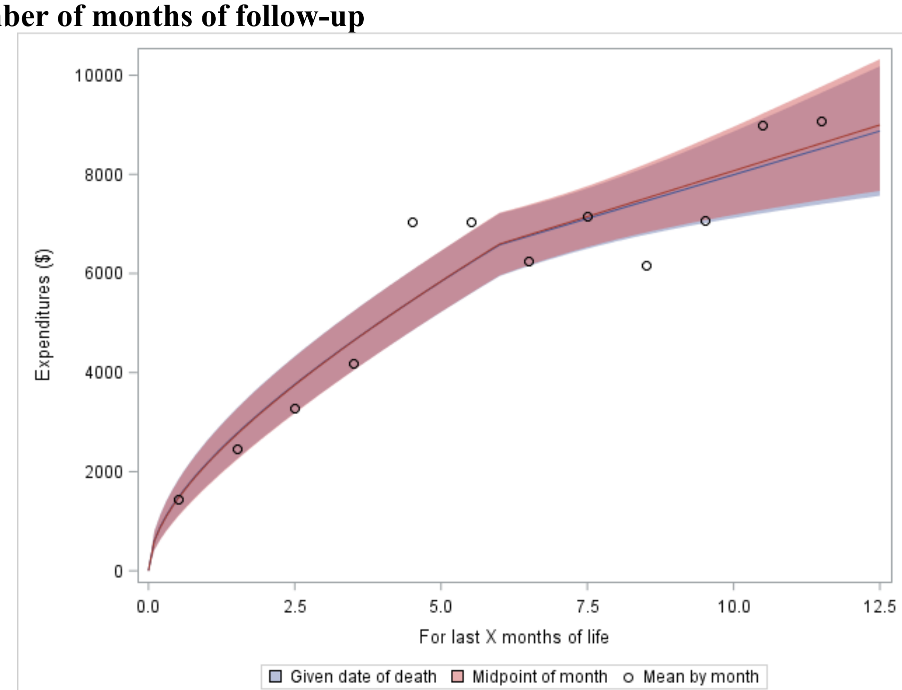


Figure 76. Regression curves for terminal year of life <u>outpatient hospital</u> expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up

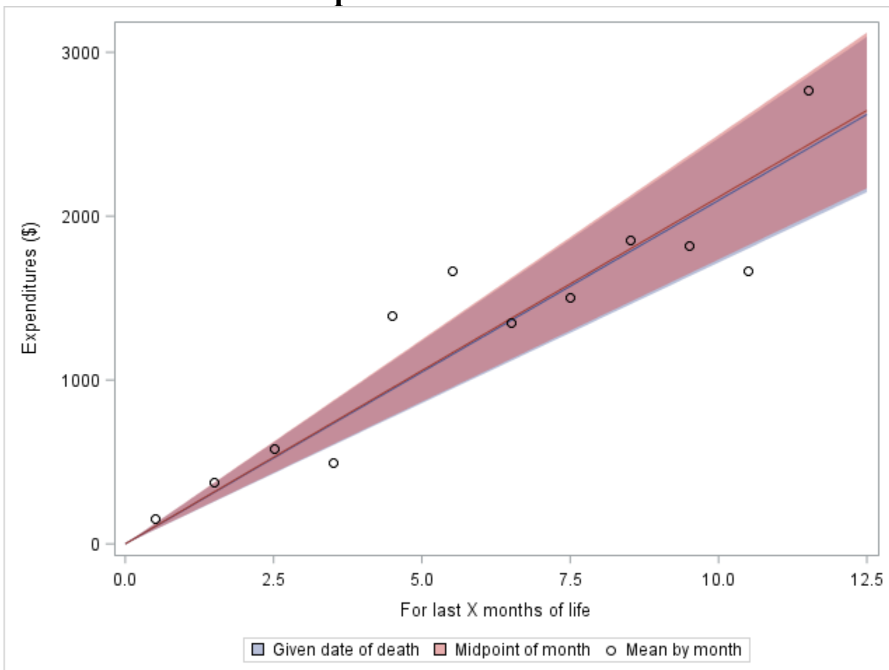
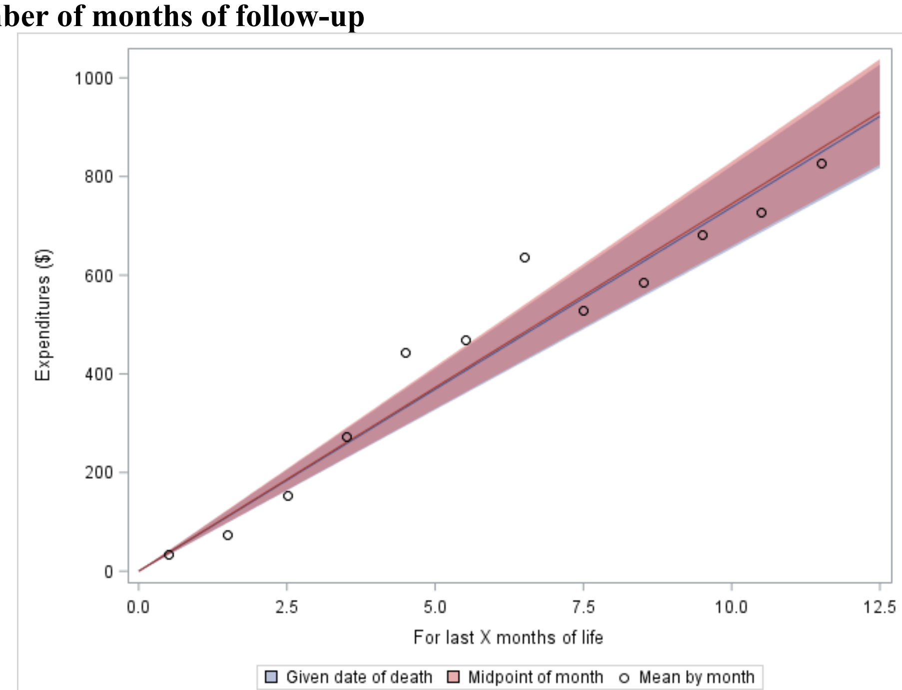


Figure 77. Regression curves for terminal year of life <u>prescribed medicine</u> expenditures using given date of death vs using midpoint of month, expenditures vs number of months of follow-up



12.2.2 Graphs of superimposed regression curves comparing linear term versus square root term in the 6-18 month analysis

Lines represent the fitted models; circles represent the averaged cumulative expenses for those with given months alive in calendar year of death. Shaded region about line represents pointwise 95% confidence band. Blue line and shaded region are for original, square root term in months model. Red line and shaded region are for linear term in months model.

Figure 78. Overlay of terminal year of life non-Medicare expenditures for 6-18 months, linear term vs square root term models, expenditures vs number of months of follow-up

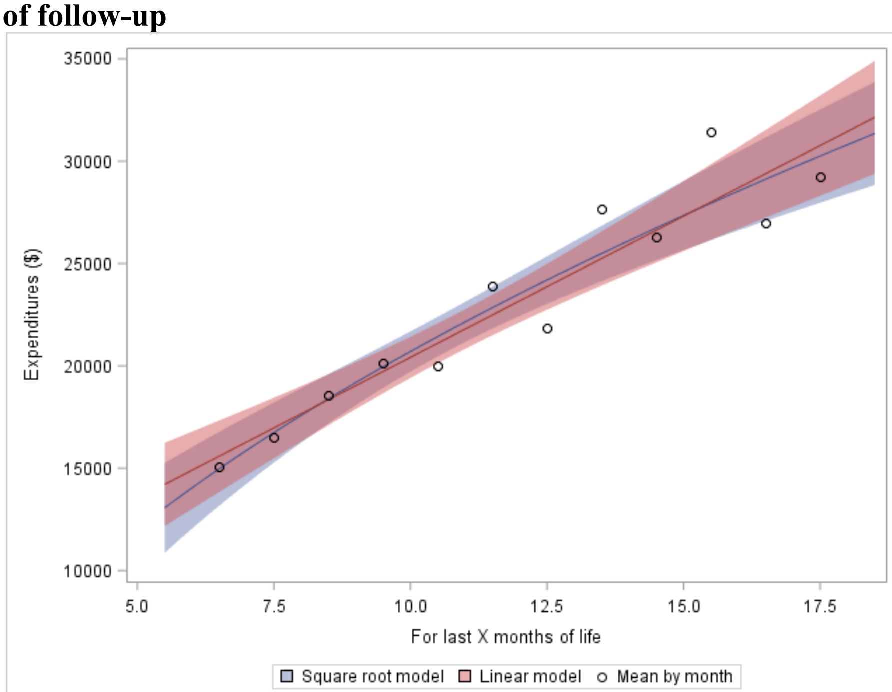


Figure 79. Overlay of total terminal year of life <u>private</u> expenditures for 6-18 months, linear term vs square root term models, expenditures vs number of months of follow-up

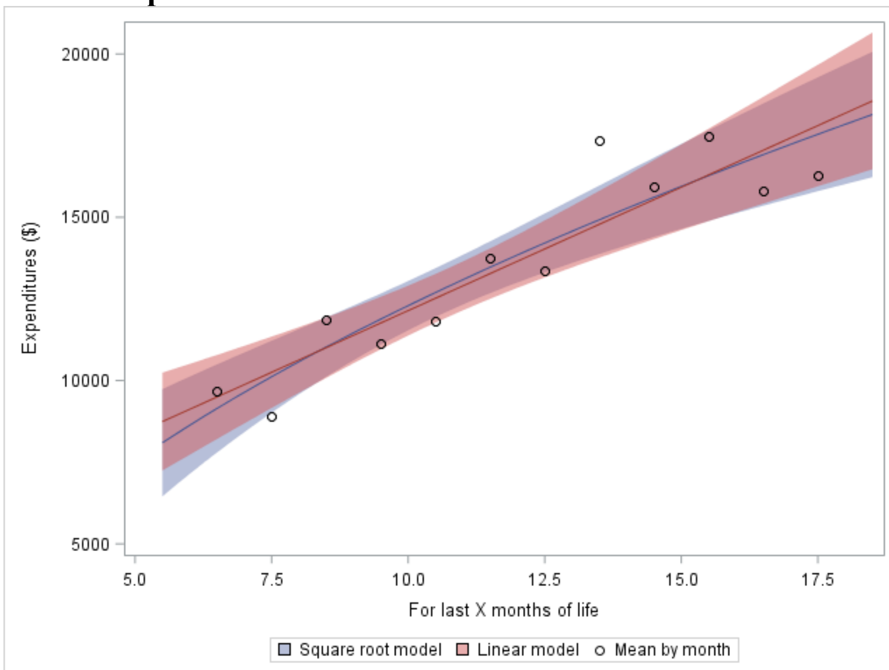


Figure 80. Overlay of terminal year of life <u>out-of-pocket</u> expenditures for 6-18 months, linear term vs square root term models, expenditures vs number of months of follow-up

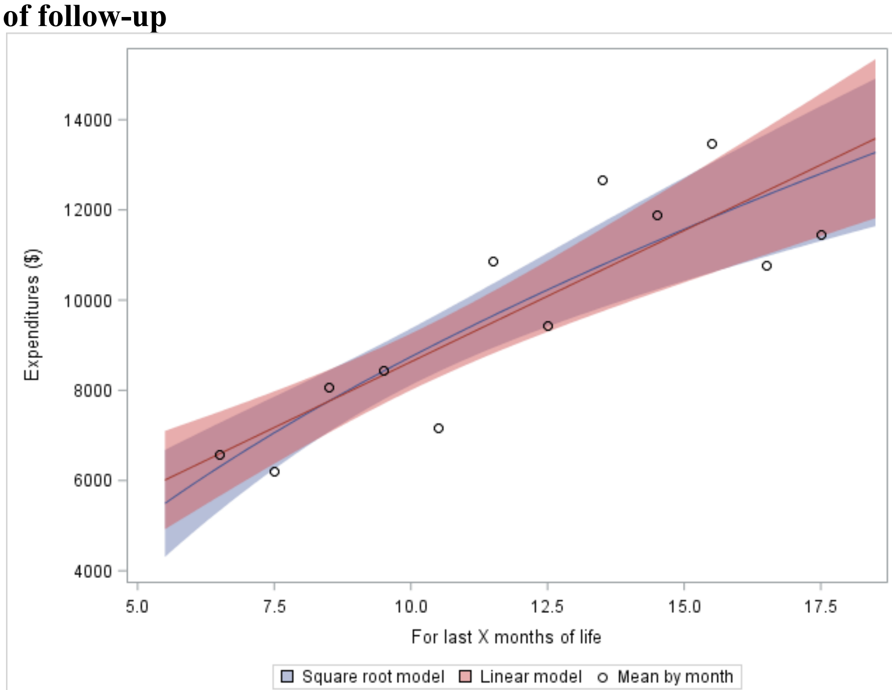


Figure 81. Overlay of terminal year of life <u>Medicaid</u> expenditures for 6-18 months, linear term vs square root term models, expenditures vs number of months of follow-up

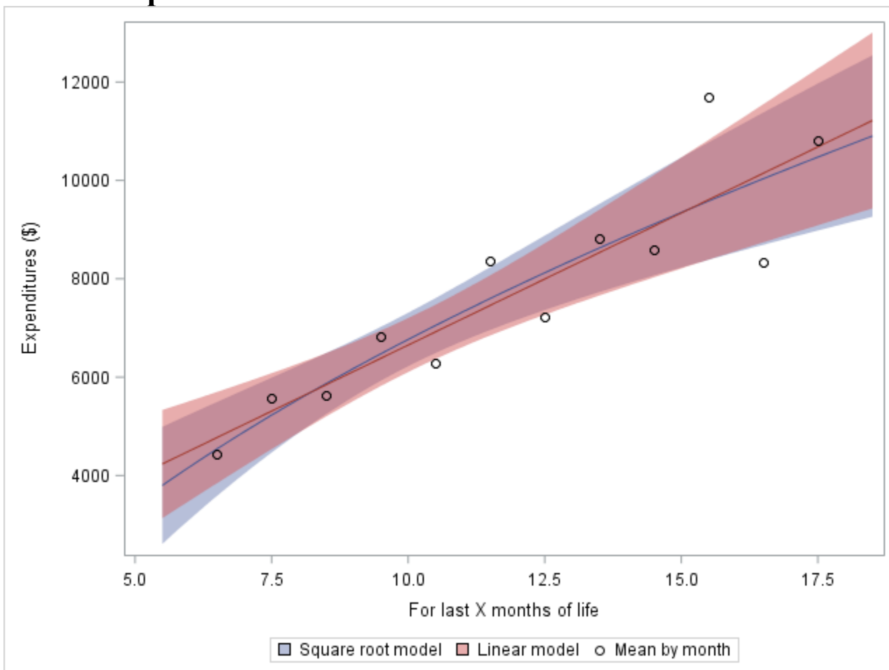


Figure 82. Overlay of total terminal year of life <u>HMO</u> expenditures for 6-18 months, linear term vs square root term models, expenditures vs number of months of follow-up

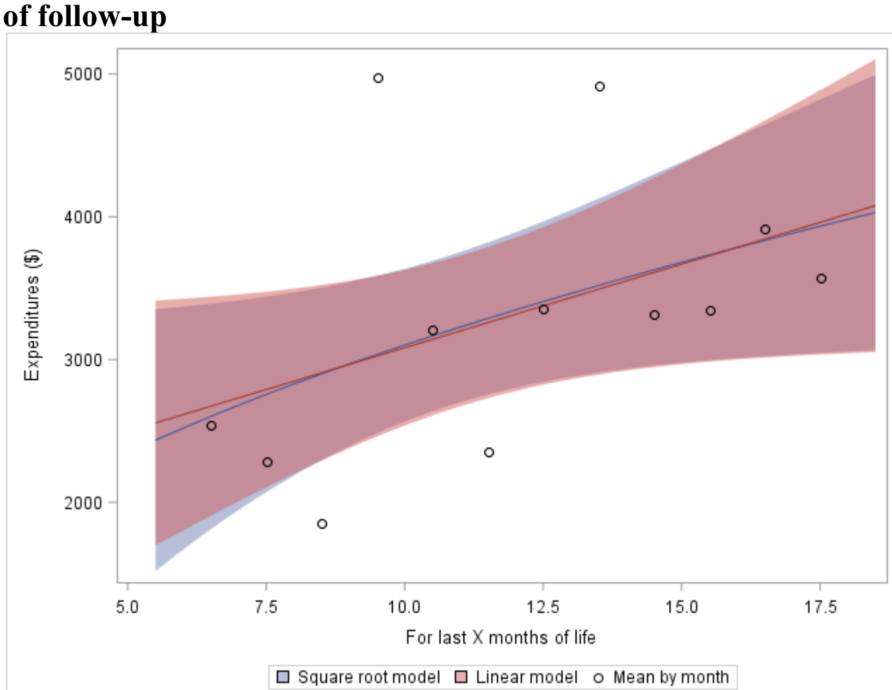


Figure 83. Overlay of terminal year of life dental expenditures for 6-18 months, linear term vs square root term models, expenditures vs number of months of follow-up

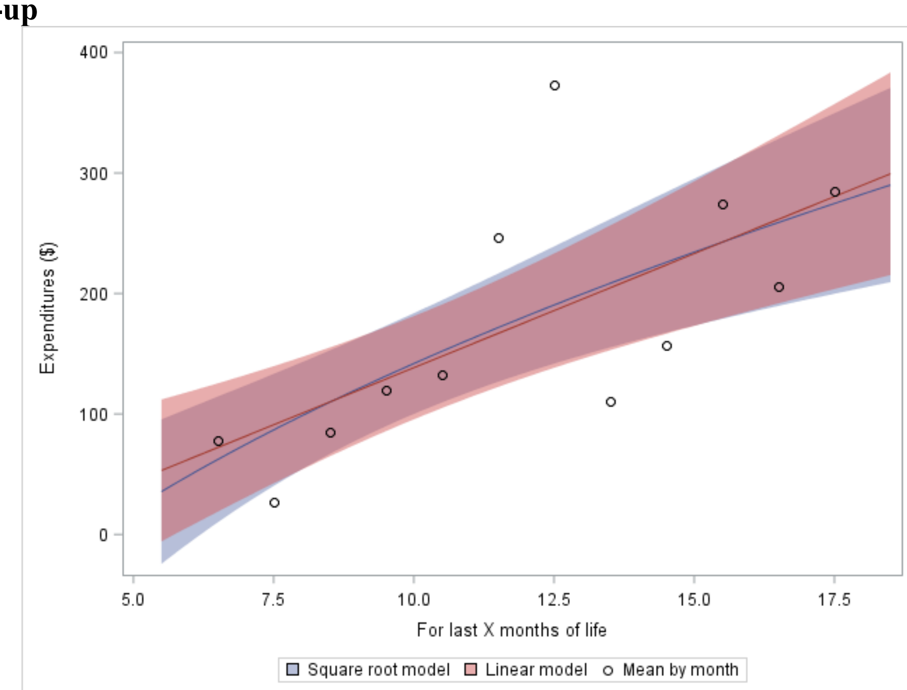


Figure 84. Overlay of terminal year of life facility expenditures for 6-18 months, linear term vs square root term models, expenditures vs number of months of follow-up

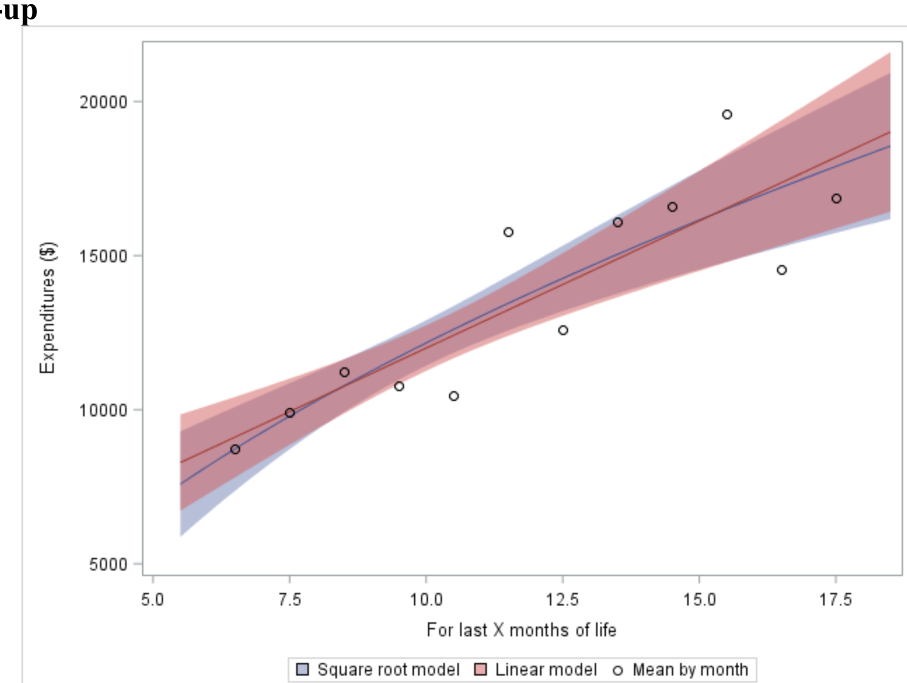


Figure 85. Overlay of terminal year of life home health expenditures for 6-18 months, linear term vs square root term models, expenditures vs number of months of follow-up

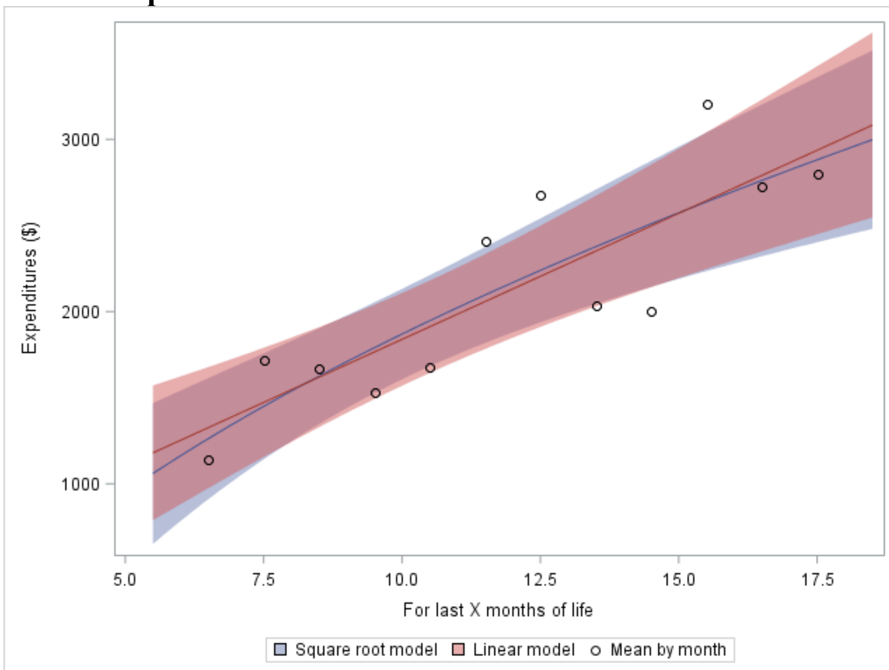
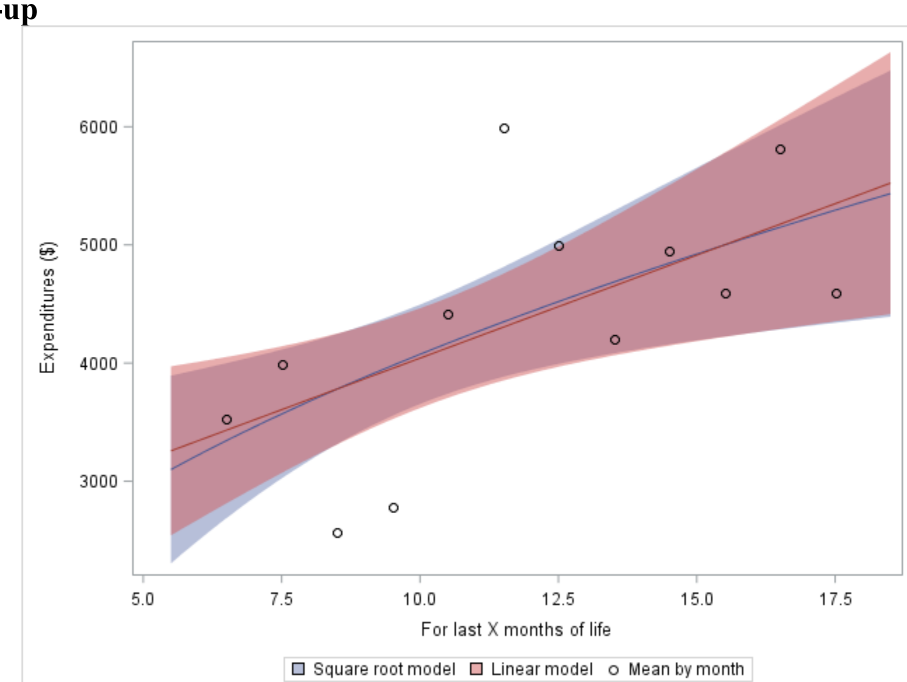


Figure 86. Overlay of terminal year of life hospice expenditures for 6-18 months, linear term vs square root term models, expenditures vs number of months of follow-up



12.2.3 Graphs of superimposed regression curves comparing model with intercept to model without intercept

Lines represent the fitted models; circles represent the averaged cumulative expenses for those with given months alive in calendar year of death. Shaded region about line represents pointwise 95% confidence band. Blue line and shaded region are for the original model with an intercept. Red line and shaded region are for the model without an intercept.

Figure 87. Overlay of total terminal year of life private expenditures for 6-18 months, without vs with intercept models, expenditures vs number of months of follow-up

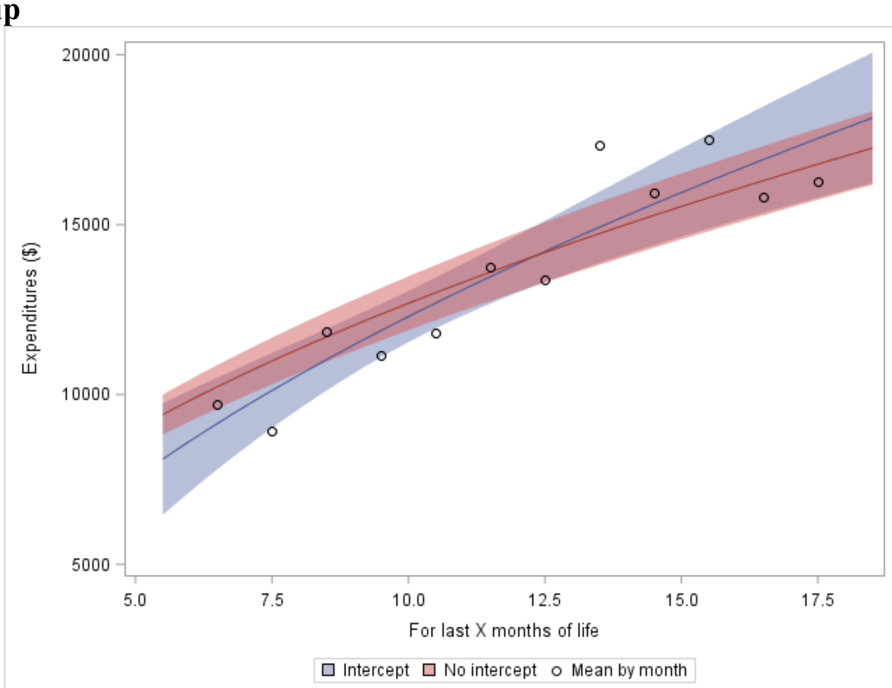


Figure 88. Overlay of terminal year of life <u>out-of-pocket</u> expenditures for 6-18 months, without vs with intercept models, expenditures vs number of months of follow-up

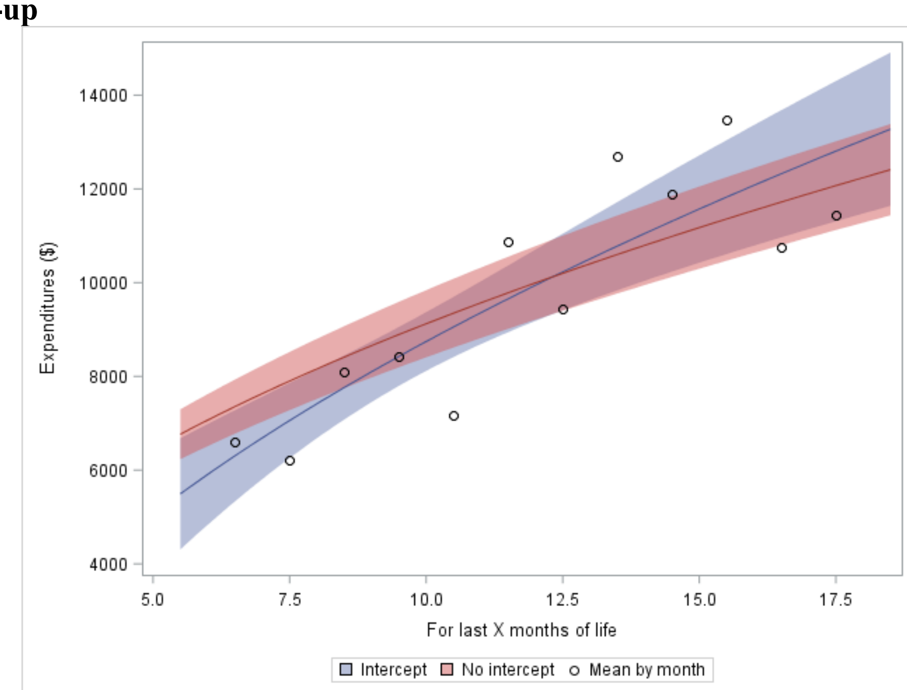


Figure 89. Overlay of total terminal year of life <u>HMO</u> expenditures for 6-18 months, without vs with intercept models, expenditures vs number of months of follow-up

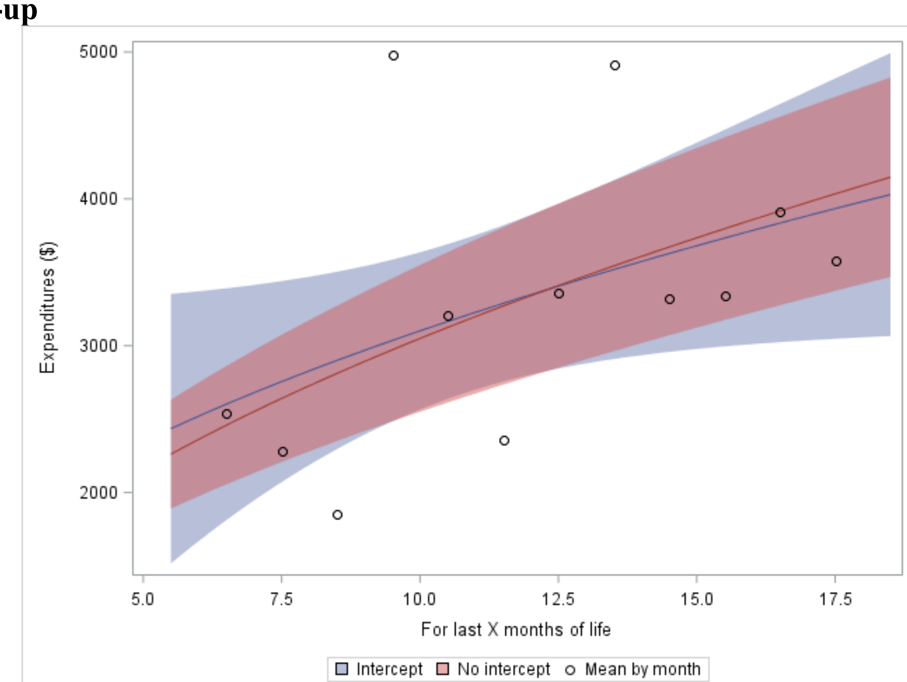


Figure 90. Overlay of terminal year of life facility expenditures for 6-18 months, without vs with intercept models, expenditures vs number of months of follow-up

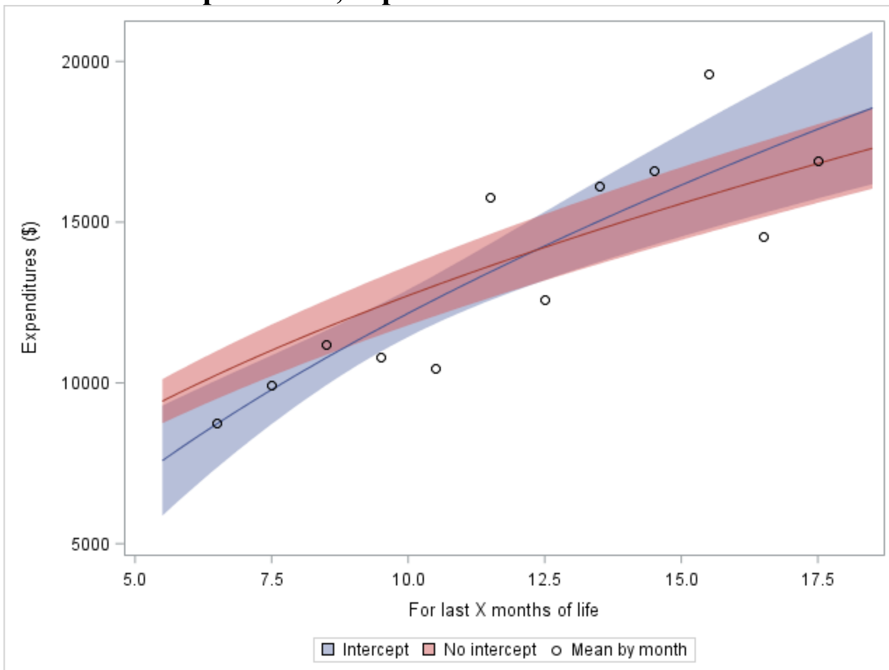


Figure 91. Overlay of terminal year of life hospice expenditures for 6-18 months, without vs with intercept models, expenditures vs number of months of follow-up

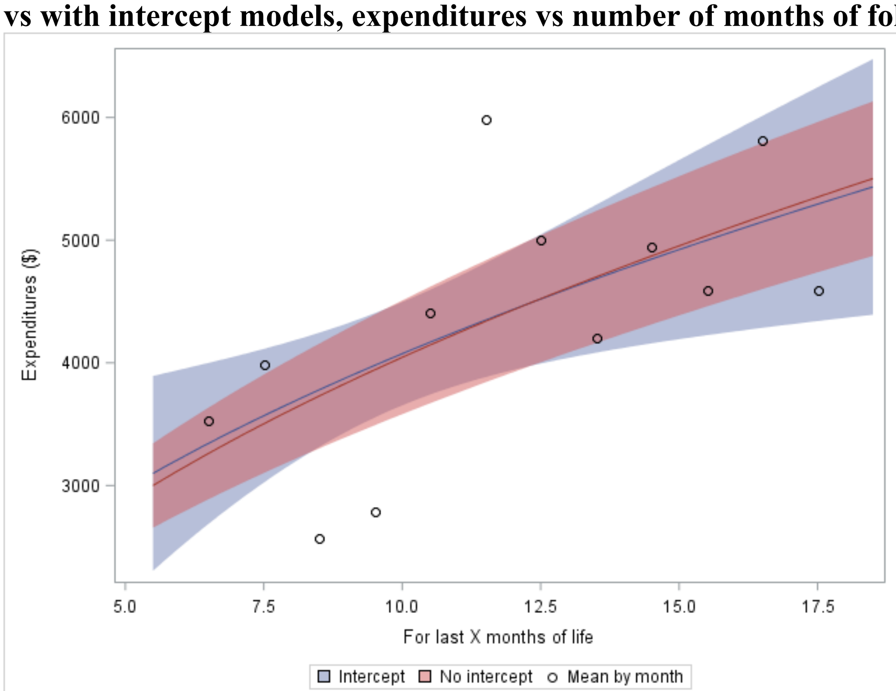


Figure 92. Overlay of terminal year of life medical provider expenditures for 6-18 months, without vs with intercept models, expenditures vs number of months of follow-up

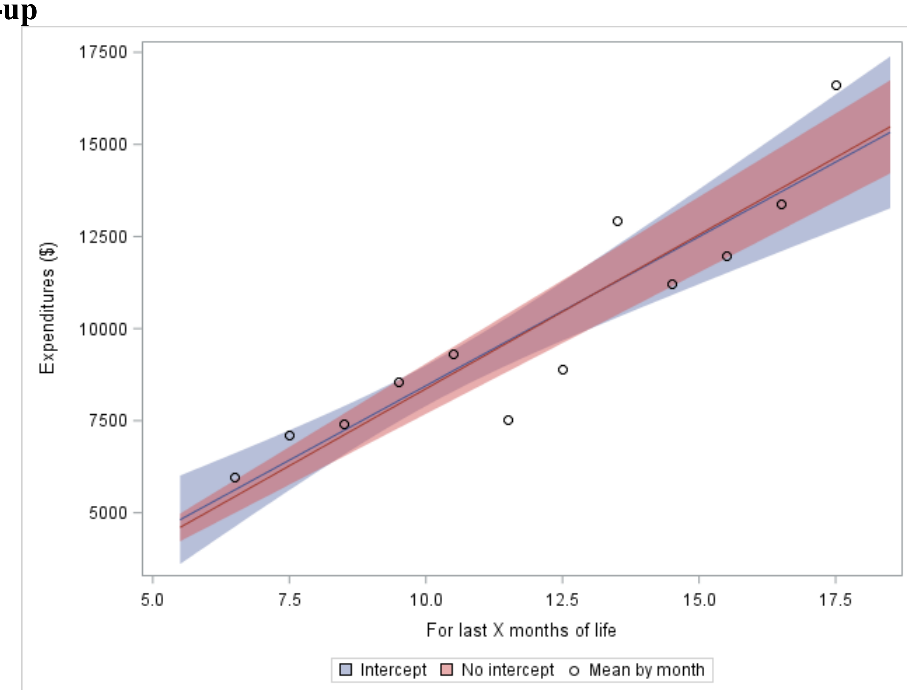
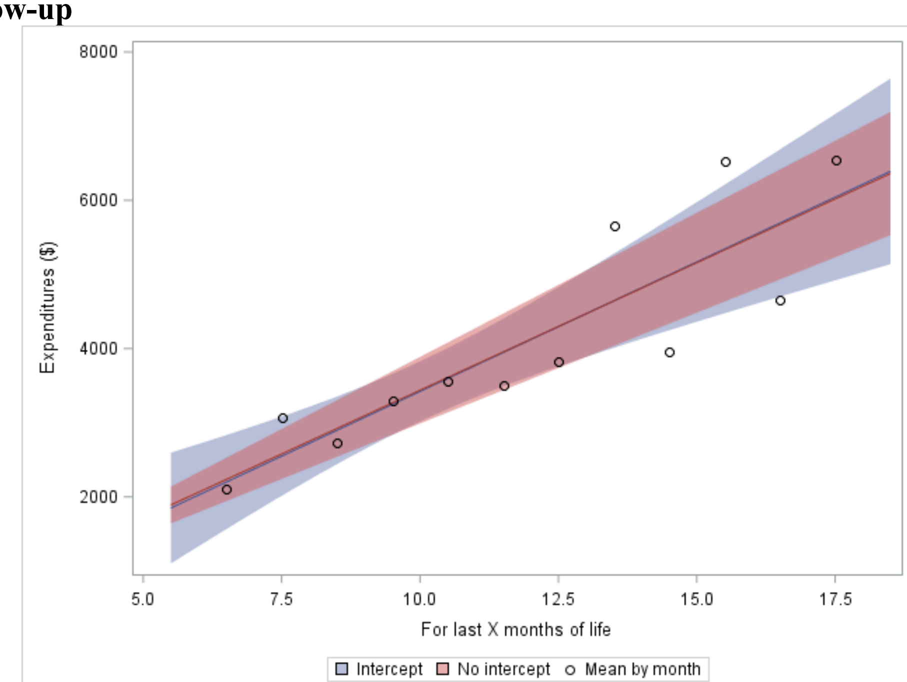


Figure 93. Overlay of terminal year of life outpatient hospital expenditures for 6-18 months, without vs with intercept models, expenditures vs number of months of follow-up



13 APPENDICES

13.1 Appendix A

Tables in this appendix give the slope effects remaining in the multiple covariate models for terminal year total, Medicare, private insurance, and Medicaid expenditures as described in Section 9.3 on page 117. Because the data was centered to 12 months for these analyses, these slope effects had no direct influence on the 12-month estimates and these terms are essentially nuisance parameters, and hence not presented in those sections. Nevertheless, for completeness, these terms (with final model p-values) and the slope parameter estimates (with standard errors) are found in the tables below. Slope effects for total terminal year expenditures are found in Table 39, Medicare expenditures in Table 40, private insurance expenditures in Table 41, and Medicaid expenditures in Table 42.

Table 39. Slope effects for linear term in months, total terminal year medical expenditures

Model term	Estimate	Standard Error	p-value
Main effect baseline slope[a]	3556	838.3	<0.0001
Age at death, change from baseline			0.0021
65-69 years	-5586	3991	
70-74 years	-50.23	7980	
75-79 years	1100	1896	
80-84 years	-602.6	2208	
85+ years	0	–	
Race, change from baseline			0.0031
Black	2987	2261	
White	0	–	
Census region, change from baseline			0.1003
Midwest	-719.9	1240	
Northeast	1906	1206	
South	-2196	1102	
West	0	–	
Age by Race interaction, change from baseline			<0.0001
65-69 years, Black	25252	6854	
70-74 years, Black	6159	7367	
75-79 years, Black	-3649	5214	
80-84 years, Black	-7520	3335	
Age by Census region interaction, change from baseline			0.0028
65-69 years, Midwest	-5437	5167	
65-69 years, Northeast	14079	7887	
65-69 years, South	4496	4587	
70-74 years, Midwest	6888	8903	
70-74 years, Northeast	-7050	10256	
70-74 years, South	71.3	7978	
75-79 years, Midwest	30.1	2881	
75-79 years, Northeast	7471	5207	
75-79 years, South	2662	2489	
80-84 years, Midwest	2161	2670	
80-84 years, Northeast	2554	3806	
80-84 years, South	1692	2644	

a Baseline slope is for beneficiary 85+, White, in the West Census region. Interactions with no effect on baseline are not listed.

Table 40. Slope effects for linear term in months, terminal year Medicare expenditures

Model term	Estimate	Standard Error	p-value
Main effect baseline slope[a]	1396	631.7	<0.0001
Age at death, change from baseline			0.0112
65-69 years	-6344	3462	
70-74 years	3809	7752	
75-79 years	1541	1814	
80-84 years	344.0	1751	
85+ years	0	–	
Race, change from baseline			0.0022
Black	3642	1771	
White	0	–	
Census region, change from baseline			0.4048
Midwest	283.9	918.5	
Northeast	1029	974.3	
South	-1291	798.1	
West	0	–	
Age by Race interaction, change from baseline			0.0001
65-69 years, Black	22385	6564	
70-74 years, Black	4787	6948	
75-79 years, Black	-2978	5214	
80-84 years, Black	-6514	2625	
Age by Census region interaction, change from baseline			0.0019
65-69 years, Midwest	-3255	4115	
65-69 years, Northeast	15434	7985	
65-69 years, South	6746	3733	
70-74 years, Midwest	1021	8433	
70-74 years, Northeast	-10431	9055	
70-74 years, South	-2762	7671	
75-79 years, Midwest	149.5	2533	
75-79 years, Northeast	6474	5138	
75-79 years, South	2086	2312	
80-84 years, Midwest	1284	2082	
80-84 years, Northeast	1514	2720	
80-84 years, South	1614	2033	

a Baseline slope is for beneficiary 85+, White, in the West Census region. Interactions with no effect on baseline are not listed.

Table 41. Slope effects for square root term in months, terminal year private expenditures

Model term	Estimate	Standard Error	p-value
Main effect baseline slope	5564	835.6	<0.0001

Table 42. Slope effects for square root term in months, terminal year Medicaid expenditures

Model term	Estimate	Standard Error	p-value
Main effect baseline slope[a]	1721	896.8	<0.0001
Sex, change from baseline			0.0048
Female	3684	1278	
Male	0	–	

a Baseline slope is for a male beneficiary.

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