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Estimating Budget Impact of Catastrophic Health Benefit Programs: Simplifying a Complex Analytical Problem

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1. Abstract

Decision-makers often request costing models in which there are different levels of cost-sharing at different tiers of annual health expenditure. Many new insurance/benefit designs internationally involve two or three tiers that involve a deductible tier (no insurance/benefit coverage), a second tier (insurance/benefit coverage with a co-pay), and possibly a third tier for catastrophic coverage (100% insurance/benefit coverage). This paper utilizes the properties of a standard log-normal distribution to develop a method for modelling private insurer or government costs of such insurance/benefit designs when decision-makers require a wide variety of scenarios. A simulation is conducted using health expenditure data from the 2013 Medical Expenditure Panel Survey (MEPS) sampling with replacement 100 samples with 1,000 observations each. Some general findings with regard to the level of skewness of the data are discussed which may assist the analyst to produce budget impact estimates.

2. Keywords: Expenditures; Skewed data; Budget impact; Cost-Sharing

3. Background

Individual-level health expenditure data are typically characterized by a positive skew, a non-trivial portion of zero values, and non-constant variance. This produces a number of methodological problems that have been addressed in the literature.1-11 The field has largely concerned itself with the methodological problems of dealing with such data in the context of regression analysis; however, there remain other issues upon which the literature has been largely silent. One of these involves how to model budget impact analyses when the data exhibit such characteristics, and when the policy direction is to estimate expenditures when cost-sharing only applies to certain ranges or tiers of expenditures.

Budget Impact Analyses (BIA) estimate the financial impact of the adoption and diffusion of a new health intervention or policy within a specific health care context.12 Normally, BIA is straightforward; the multiplication of price or cost per unit by the quantity or number of people utilizing the end product (i.e., cost = average expenditure x quantity). Often, this calculation is made in the context of computing the net cost of replacing an older health care intervention with a newer one; however, sometimes a budget impact analysis simply estimates the costs of a de novo health care program. While it may seem simple, the process of obtaining each of these two components—average expenditure and quantity--is not trivial as it involves understanding the policy context, issues regarding expected uptake, adjusting for risk, the level and range over which cost-sharing is instituted and other issues which are only complicated by skewed beneficiary expenditure data. The most recent Budget Impact Task Force Report is focused on producing guidelines for estimating the budget impact of new health care technologies and does not give sufficient guidance regarding the estimation of impact on an insurer or government body of changes in the benefit structure 12. For example, many major insurers have moved more toward a catastrophic insurance model with high deductibles in the range of $5,000 per person in the United States and up to 2,500 CHF ($2,400) in Switzerland with limited coverage thereafter until a threshold is attained at which full coverage may be provided. As well, the Canadian provincial governments in British Columbia and New Brunswick have moved away from providing seniors with full drug coverage and made coverage contingent on drug expenditures as a percentage of income across the age spectrum with different levels of coverage as expenditures exceed different percentages of income.

A study interviewing key decision-makers in British Columbia, shortly after their Fair Pharma Care prescription drug tiered benefit was introduced in May 2003, found that the program parameters for cost- sharing and income-testing were established after preliminary cost estimates were found to be too low.

Partially as a result of this inverted policy process, one of the three key constraints that determined the success or failure of the policy was meeting unreasonable budget constraints [13]. This underscores the importance and practical application of carrying out statistically valid BIA when cost-sharing applies to a limited range of expenditures.

With such tiered benefit designs, there is an inherent difficulty in estimating the impact on the third- party payer given the skew in expenditure data normally used to model budget impact. Often, the expenditure data used for modelling the budget impact of a new program or change in benefit structure are from a related currently-existing program. When attempting to produce such budget impact estimates, the structure of coverage--with up-front annual deductibles, expenditure ranges over which co-pays apply, and even expenditure ranges over which full coverage applies—complicates the budget impact analysis which requires separate analyses for each tier of coverage. Further, if we relax the assumption that health seeking behavior remains static, an additional adjustment should be made to expected expenditures based on both income level and changes in out-of-pocket expenditure effects.

This paper attempts to provide some analytical guidance for using such data to help inform the likely budget impact on a third-party payer when providing various health benefits and insurance products. More specifically, it provides improved methods for predicting program expenditures when a health insurer changes the deductibles and co-pay rules or when a government designs a new health benefit program with various tiers of coverage depending only on the level of expenditures.

3.1. Analytical Issue

There are many occasions when economists and policy analysts are requested to model the cost of a proposed program based on data from an existing related program from which access to the data held at a data centre is limited to one or two requests for calculations. Often, these estimates will involve a portion of annual expenditures subject to a co-payment by the patient. The patient is expected to pay full cost until the lower limit (i.e. the deductible) is attained; and beyond the upper limit--often considered a catastrophic threshold--the patient faces no out-of-pocket costs. Further, the decision-maker can often change directions regarding these limits and request a budget impact estimate for each alteration.

Many health insurance products in the United States and elsewhere are now designed to provide catastrophic coverage (i.e. with high deductibles and then either complete or partial coverage thereafter). Some, but not all, of these policies have a third tier beyond which the patient faces no out-of-pocket expenditures as illustrated in Figure 1 below.

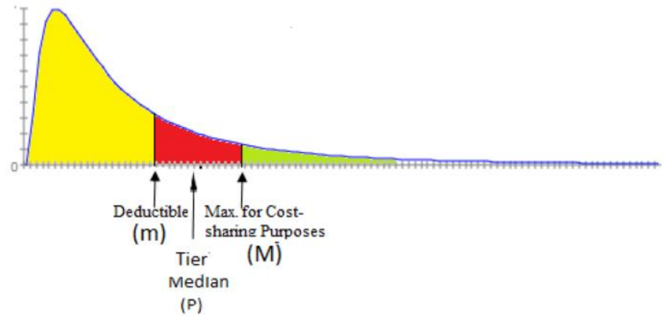

Figure 1: Hypothetical Skewed Health Expenditure Distribution with Three Tiers.

An example of such a policy structure is the Fair Pharmacare Program in British Columbia, Canada. It is a government-sponsored program with eligibility based on income. Deductibles are set at expenditures of 2% of net income and cost-sharing occurs for expenditures that fall within 2% and 3% of net income. There is no cost-sharing (i.e. 100% coverage) beyond 3%. Furthermore, many health insurance policies written by Anthem, Inc. and other private insurers in the United States and elsewhere are catastrophic programs that have a per-service co-pay beyond a large deductible; they are therefore considered two-tier insurance programs.

3.2. Literature Review

Orlewska et al. (2009) highlight the increasing number of budget impact analyses appearing in peer-reviewed journals which is providing impetus for further improvement, validation and distribution of research findings [14]. Their review also points out that many current analyses fall short of reaching publication quality, however it suggests that this situation will change as improved standards and techniques are established that assist in clarifying and codifying important issues [13]. As such analyses become more common in the literature, improved techniques for BIA need to be developed and adopted. This was recommended in the Budget Impact Analysis ISPOR guidelines, and echoed in calls for adoption of a more comprehensive approach including how to combine multiple data sources, statistical challenges involving heavily right-skewed cost data, and effective approaches for reporting findings [12,15,16].

Additionally, an important policy issue related to skewed data involves understanding the characteristics of individuals who occupy the right-tail of the expenditure distribution. A recent study by Rosella et al. (2014) outlined the characteristics of high-cost users of health care in Canada and showed a highly positively skewed distribution [17]. Most recently, there are a number of articles that have examined shifts in the health expenditure distribution beyond just the mean. De Meijer et al. (2013) separate out changes in the distribution of Dutch health expenditures across time using methods developed by Chernozhukovet al. (2013) [18,19]. They find two sources of variation in the distribution over time:

(1) the distribution of the underlying characteristics--co-variates--of the population and

(2) structural changes in the relationship between the co-variates and the distribution of health expenditures [18].

In essence, they find that both the covariates themselves and their effect on health expenditures vary over time and across the distribution of health expenditures which would have been missed if the analysis were confined to the mean as has been traditionally the case. They also find that pharmaceutical costs are increasingly large in the upper tail of the distribution due to structural shifts; yet, growth in hospital costs are mainly confined to the center of the expenditure distribution due to changes in the distribution of the covariates [18]. Andrew Jones and colleagues (2015) expand on this work by testing various parametric distributions fit to health expenditures in the British National Health Service [20]. Most pertinently, they find that the log-normal is a highly efficient at estimating health expenditures but is inconsistent as it tends to underestimate expenditures at the upper end of the distribution [20].

4. Data and Methods

4.1. Data

Total health expenditure—i.e., insured and out-of-pocket expenditure--data for individual residents of the United States were sampled from the Medical Expenditure Panel Survey (MEPS) for the year 2013. Based on approximately 38% of the National Health Interview Survey panel (n=36,940), the MEPS provides a nationally representative weighted sample representing over 315 million Americans. The following provides the unweighted and weighted distributions regarding total health expenditures- the sum of out-of-pocket and third-party health expenditures [21].

Value	Unweighted	Weighted
$1-$311	7,831	49,257,746
$312 - $1,020	7,288	53,340,859
$1,021 - $3,645	7,271	62,037,344
$3,646 -$514,670	7,273`	72,781,801
Total	36,940	315,721,982

The 36,940 observations in the 2013 MEPS are sampled with replacement to produce 100 samples each with 1,000 individuals and their overall health care expenditures for that year. The unweighted data are used as the original weights provided are no longer valid when considering subsamples of the data for which a new set of weights are needed to represent the corresponding segment of the population; moreover, these weights are not needed for the purposes of the simulations conducted herein. One of the sample distributions is given below in Figure 2.

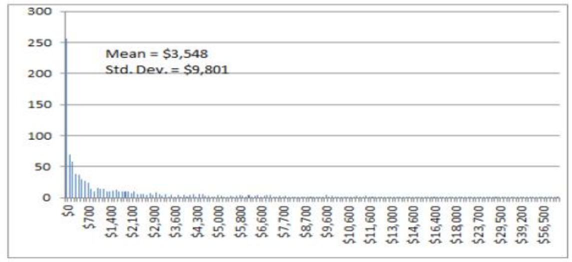

Figure 2: A sample of 1,000 observations from the MEPS (2013) data

4.2. Methods

The skewness of a distribution impacts the mean expenditure (or central tendency) within each of its tiers with greater skewness shifting the central tendencies further leftward. To measure skewness, a variety of general measures are available including the very intuitive Pearson's First and Second Moment Coefficients [22]:

1) $3*(\mu-o)/\theta$

2) $3*(\mu-\nu)/\theta$

where μ is the arithmetic mean, ν is the median value, o is the statistical mode and θ is the scale parameter known as the standard deviation.

Also, the adjusted Fisher-Pearson standardized moment coefficient (G_1) is also utilized by major software packages like SPSS, SAS, and STATA[23]:

$$G_1 = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}}{S} \right)^3$$

Which is equivalent to

$$G_1 = \frac{\sqrt{n(n-1)}}{n-2} \left[\frac{\frac{1}{n}\sum_{i-1}^{n}(x_i-\bar{x})^3}{\left(\frac{1}{n}\sum_{i-1}^{n}(x_i-\bar{x})^2\right)^{3/2}} \right]$$

where n is the sample size and x-bar is the sample mean and s is the sample standard deviation.

While there is both intuitive appeal to the Pearson Moment Coefficients and no need to access the original data sample for calculations, they lack statistical power to determine differences in skewness between distributions. This lack of statistical power has caused major software packages to adopt G_1 as a measure of skewness [24]. Bowing to this trend, this paper utilizes G_1 as an empirical measure of skewness needed to estimate mean values specific to a particular segment or tier of the distribution.

When segmenting each sample into different tiers, the cost-sharing tier was defined as the segment between the 500^{th} (the median) and 900^{th} observation corresponding to the 50^{th} and 90^{th} percentile of values in each sample. The deductible was defined as expenditures up to the median level of expenditures, and the catastrophic coverage tier (100% coverage) was defined as expenditures exceeding the 90^{th} percentile of expenditures.

4.1. Determination of Cost-Sharing Tier's Mean Expenditure

The budget impact analyst must either use data provided to calculate the mean expenditure (P) (e.g., expenditure per person, or per family) for a particular expenditure tier or develop an alternative measure that is reliably close to the calculated mean. (Thereafter, the mean cost to the third-party payer is simply a percentage of this figure reflecting the cost-sharing scheme employed.) The paper aims to develop such an alternative measure for P specific to the cost-sharing tier so as to limit reliance on data canter resources to recalculate such means every time the decision-maker requests changes in the magnitude of this tier. Therefore, an alternative measure of central tendency equivalent to the mean expenditure over this tier is needed. A measure of central tendency takes the form:

$(M – m)/ \alpha$

Where M signifies the maximum expenditure in the tier, m the minimum expenditure, and α an adjustment factor. The median of the tier would have an α of 2, which in a normally or uniformly distributed distribution, would be equivalent to the mean. Since these cost-sharing tiers likely also exhibit properties of skewness beyond the skewness of the entire distribution of expenditures, it is likely that $\alpha > 2$. The question is how much greater. To determine equivalency, α can be expressed as follows:

$P = m + (M – m)/ \alpha$

$\alpha = (M-m)/(P – m)$

From the perspective of the third-party payor, the average expenditure is then the percentage of the expenditures that they bear according to the cost-sharing structure established. This value can be labeled P_share.

To predict α, OLS linear regression techniques can be utilized to regress α on G_1 of the designated tier or on a highly correlated proxy. We propose that the domain of the cost-sharing tier anchored by the coefficient of variation (θ/μ) of the entire expenditure distribution--referred to here as the "anchored distance" (D_A)--is a potential candidate proxy:

$DA = (M – m)\ \theta/\mu$

The motivation for using such a measure is that a larger tier would naturally be associated with a larger value for the partial skew if the overall distribution is skewed. Just as the coefficient of variation is a standard measure of dispersion, this measure serves much the same purpose for segments of distributions. Additionally, highly skewed distributions are likely to have high coefficients of variation and thus higher values for this measure. Lastly, unlike G_1, the calculation of D_A does not require data center resources to recalculate a value each time a decision-maker adjusts the endpoints of the cost-sharing tier.

The regression model to produce estimates of the adjustment factor (α)--and therefrom estimates of P (P_hat)--is as follows:

$ai = \beta_0 + \beta_1 D_{Ai} + \varepsilon$

The performance of the estimation method is tested by assessing the percent error between the estimated mean expenditure (P_hat) for a sample's cost-sharing tier and the corresponding actual mean expenditure (P) of that sample's cost-sharing tier. As well, the rate of convergence to assess the statistical

efficiency and consistency of the estimator is assessed using the formula for the variance:

$$\sum_{i=1}^{n} \frac{(\text{P\_hati} - \bar{\text{P}})^2}{n}$$

Where $\bar{P}$ is the cost-sharing tier mean expenditure for all 36,940 observations in the 2013 MEPS ($2,541.75). It is assumed that if the variance appears to converge at a certain number of sampling replications, then the number of replications is considered sufficient to establish the efficiency and consistency of the estimator.

4.2. Determination of the Expected Quantity

To determine a measure for Q (e.g., units of service, utilizing people, or utilizing families), it is generally best to try to transform a skewed distribution using a natural logarithmic transform so as to be able to work with the standard normal distribution if the underlying distribution is close to being log-normal. A hypothetical transformed log-normal three-tier distribution is illustrated below in Figure 3.

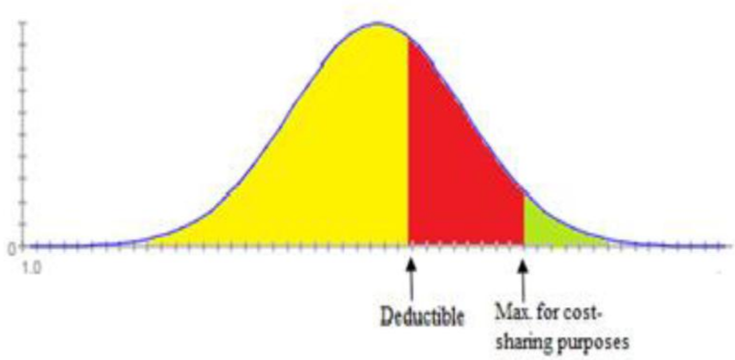

Figure 3: Hypothetical Transformed Log-Normal Health Expenditure Distribution with Three Tiers

Log-normality can be roughly determined if the log-transformed data used to model program expenditures has a median (ν) and mean (μ) which are equivalent or close to equivalent based on a visual examination of these statistics in relation to their magnitude. If so, the standard normal table can be utilized to determine the percentage of the units of analysis that are expected to fall within the specified cost-sharing tier. The natural log of the minimum (m) of the tier and the maximum (M) of the tier are calculated and divided by the standard deviation (s) of the log-transformed expenditure data to produce standardized estimates of these cut-points for this log-transformed distribution. A standard normal z-table can be used to determine the percentage of observations, people, or families expected to fall within the cost-sharing tier.

The analyses in this study used both Excel v. 14 and STATA v. 12 [23,25]

5. Results

The summary statistics for the simulated distributions are contained in Table 1 below:

Table 1: Descriptive Statistics.

Variable	n	Mean	Standard Deviation	Minimum	Maximum
Mean of Expenditures (μ)	100	$3532.69	$373.46	$2351.46	$4367.49
Mean of Expenditures in Cost-sharing Tier (P)	100	$2,525.18	$201.24	$2,125.50	$2,990.37
Estimated Mean of Expenditures in Cost- sharing Tier (P_hat)	100	$2521.97	$201.71	2,098.65	$3,054.51
% error	100	-0.02%	4.77%	-10.50%	13.43%
Standard Deviation of Expenditures (θ)	100	$11,042.19	$2,967.63	$1,877.22	$21,769.55
Median of Expenditures (ν)	100	$536.13	$55.29	$323.00	$685.00
Coefficient of Variation	100	3.09	0.62	0.8	5.29
G_1 measure of skew	100	9.1	3.5	3.62	21.72
G_1 (cost-sharing tier skew)	100	1.17	0.12	0.8	1.43
Pearson's 2nd Moment Coefficient of Skewness	100	0.86	0.24	0.49	2.96
Anchored Distance (DA)	100	24,108.96	4,963.60	6,305.12	43,887.41
Adjustment factor (α)	100	3.94	0.25	3.37	4.77

The mean values for the untransformed data include those for the overall mean ($3,532.69), the mean for the cost-sharing tier of ($2,525,18) and the estimated mean for this tier of $2,521.97). The standard deviation of expenditures averaged $11,042.19. It is important to note that the mean and median are $3,532.69 and $536.13, respectively, suggesting a highly skewed distribution of expenditures. The log- transformed data produces overall mean and median values that are within 1.9 (8.3--mean vs. 6.2--median) of each other suggesting that log-normality is not an unreasonable assumption for these data although it is likely that the transformed data would underestimate the number of individuals in the upper tail of the distribution. The coefficient of variation (θ/μ)—a standardized measure of dispersion-- averages 3.09 with a minimum of 0.80 and maximum of 5.29. The summary data indicate that the calculated adjustment factor in these simulations varied from 3.37 to a maximum of 4.77 with a mean adjustment for dividing the cost- sharing tier of 3.94. The various measures of skewness are all positive indicating a positive skew for all of the simulations even though the magnitude of these measures vary considerably as there is no one correct skewness measure [26]. The anchored distance (D_A) average is 24,108.96 with a standard deviation of 4,963.60, a minimum of 6,305.12 and a maximum of 43,887.41.

The estimator for the tier-specific mean expenditure is generally very precise with an average error from the sample's tier-specific mean expenditure of just -0.02% with 95% of the estimates within ±9.3%

Table 2 suggests that G_1 and D_A are significantly correlated suggesting that the anchored distance can serve as a proxy measure of G_1 in a linear regression estimation.

Table 2: Pearson Correlation Statistics between Skewness Measure G_1 and Anchored Distance (D_A)

	G_1 (cost-sharing tier skew)	Anchored Distance (D_A)
G_1 (cost-sharing tier skew)	1.00**	0.29**
Anchored Distance (D_A)	0.29**	1.00**

**p < 0.01

The OLS regression results in Table 3 suggest that a $10,000 increase in DA is associated with a 7.71% leftward shift in the average expenditure from the median with the adjustment factor approaching 2 (the median) as $\lim_{M\to m} D_A = 0$. Further, the results in Table 4 show that the estimator converges at approximately 100 replications, the number used in the analyses.

Table 3: OLS linear regression results of regressing adjustment factor (α) on anchored distance (D_A) (n =100)

Dependent Variable Adjustment factor	Coefficient (Std. Error)
Anchored Distance (β_1)	0.0000167** (0.0000046)
Constant (β_0)	3.54** (0.15)

R-sqr (adj) = 0.11**
*p < 0.05 **p < 0.01

Table 4: Convergence of Estimator as Resampling Replications Increase toward 100 samples.

Samples (n)	Variance $\sum_{i=1}^{n} \frac{(\text{P\_hati} - \bar{\text{P}})^2}{n}$
25	52,938.54
50	46,327.48
75	42,945.50
100	40,673.18

The determination of Q is a simple exercise in utilizing standard normal z-tables after transforming the maximum and minimum values of the cost-sharing tier using natural log transforms and finding the area of the tier underneath the standard normal Gaussian (histogram).

6. Discussion

The results of this simulation suggest that the analyst wishing to model the expected budget impact on the payer of a two or three-tiered insurance policy utilizing skewed expenditure data can reliably – and relatively simply - do so utilizing the methods provided. The adjustment factor to determine measures of central tendency in the cost-sharing tier can be predicted based on the anchored distance (D_A) of the tier— a measure that does not require access to the original data of the distribution, but rather only a few summary statistics. A 10,000-unit increase in this measure is associated with a 0.167 increase in the adjustment factor, α, needed to reliably produce a measure of central tendency for this cost-sharing tier.

This increase is associated with an 8.4% [=0.167/2] leftward shift of the mean value from the tier's median. Performance of this estimator for mean expenditure is quite precise with errors averaging just 0.2% and the range of error was well within the risk-corridor that could trigger reinsurance pay-outs. When combined with the measure of Q obtained from a standard-normal z-table, the analyst can produce an accurate measure of P_share * Q for the cost-sharing tier. When considering only two-tier insurance programs--with the upper tier consisting of full-coverage and the lower tier with either no or minimal coverage--the upper limit of the second tier can be placed somewhere between 2.5θ and 3θ to limit the influence of extreme outliers on the measure of central tendency. These outliers can then be counted and summed separately in a single data request.

Further, while the domain of the cost sharing tier in this analysis is fixed in terms of the percentiles that the lowest (50^{th}) and highest (90^{th}) values represent, the magnitude of the domain, in absolute terms, varies between the samples. The domain of the cost-sharing tier amongst the 100 samples ranges from $6,307 to $9,484—a sufficient range to suggest that the methodology is robust to differences in tier size.

Obtaining a precise estimate for the adjustment factor (α) is important as it has significant implications for either overestimating or underestimating budget impact. For instance, if α is undervalued at 2.5, then the estimate for government expenditures may exceed total expenditures including the expected out-of-pocket amount expended by beneficiaries; therefore, it is important to obtain relatively precise estimates for α when conducting budget impact analyses for tiered benefit programs.

Among the limitations, there is a concern that the log-normal distribution, though precise, is biased downward particularly with regard to the right tail of the distribution; as a result, any budget impact analysis of the catastrophic third tier may have to rely on traditional calculations using the actual data rather than the estimation technique suggested herein [21]. Given the small number of people who might have annual expenditures in the catastrophic tier, however, any bias may not be sufficient to have an appreciable impact on the precision of the overall estimated cost—across the second and third tiers--of an insurance/benefit program. Second, the analysis used unweighted observations in each of the subsamples. In fact, it might be possible to use weights when computing various moments of samples obtained through re-sampling of survey data. These weights need to be recalculated based on the knowledge of the underlying population post-stratified according to demographic information in the same way as the original sampling design weights to obtain the final bootstrap weights [27].

In the end, the MEPS data may not be representative of the distribution of health expenditures in other countries where health technology and advanced medical care are not as readily available as in the United States [28]. As a result, the skewness of health expenditure distributions may vary across jurisdictions and the samples obtained in this study may not be representative of the shape of health expenditure distributions elsewhere. This suggests the need to apply these methods to health expenditure data in other countries to determine whether the results and associations obtained remain valid internationally. In particular, future work might examine less highly skewed distributions to determine if a similar relationship to the one calculated between α and D_A persists. As well, a real-world evaluation of how well such modelling techniques predict costs post-implementation would be the ultimate test of the usefulness of the proposed methods.

A further issue, as noted by Basu and Manning (2009), is that there needs to be more attention paid to developing models that reliably predict the cost of different groups of people or even particular individuals rather than those simply calibrating the overall mean to ensure that it is correct [29]. The model developed in this paper can incorporate some variability because of changes in demand due to variability along a number of axes. The most common ones, from an economics perspective, deal with the effects of changes in out-of-pocket price due to cost-sharing and the impact of differences in income across the population of interest. The RAND Health Experiment provides multiple estimates of both price and income elasticities that might be useful in adjusting, for example, data that was based on one particular population (e.g., those with lower incomes) for other populations [30]. Other types of related measures that provide a utilization gradient by income or out-of-pocket cost can be obtained from examples in the literature across various health care markets—for example dental, prescription drugs, and vision care [31-33]. All of these adjustments can be made to the base case to allow for segmenting the analysis for specific subpopulations or even to individuals based on more specific types of risk adjustment.1 Adding such adjustments for changes in health seeking behavior, may increase the accuracy of the methods proposed.

7. Conclusion

In summary, the following steps are necessary for utilizing this method:

1. First check if the data is approximately log-normal by asking the data center to produce log- transformation of the data and provide mean and median values. If these are close in value, then log-normality can be assumed.
2. Calculate the mean and standard deviation for the entire distribution of expenditures from which the coefficient of variation can be calculated

3. Determine the domain of the cost-sharing tier (maximum (M) and minimum (m)
4. Combine steps 3 and 4 to calculate the anchored distance (D_A).
5. Multiply the anchored distance by 0.0000167 (regression coefficient obtained in the analyses herein) and add the regression constant of 3.54 to determine the adjustment factor, α.
6. Using the formula: $P = m + (M – m)/ \alpha$, estimate the cost-sharing tier's mean expenditure (P_hat)
7. Multiply P_hat by the percentage of the expenditure born by the third-party payer to obtain the average expenditure it bears for cost-shared expenditures. This is P_share
8. Take the log-transformation of the expenditure distribution and use a standard-normal z-table to determine the percentage of the annual expenditure observations (i.e., individuals or families) that lie within the cost-sharing tier. This will produce a value for Q
9. Multiply P_share by Q to determine expected cost associated with cost-sharing tier.
10. For a new initiative, this value represents the expected cost associated with the cost-sharing tier. If the initiative reflects a change in benefit structure, this value can be compared with the expenditures associated with the current cost-sharing structure to determine any change in budget impact.

This simulation exercise represents a first attempt to provide the analyst with tools to undertake a budget impact analysis of a proposed three-tiered health benefit/insurance program when only a few summary statistics are available to the analyst. This may be due to concerns either over the proprietary nature of the original data or privacy legislation that restrict its release to prevent identification of individuals. This result suggests that if the analyst has access to the maximum and minimum of the cost-sharing tier (often provided by decision-makers) and the coefficient of variation of the overall distribution, they can reliably predict the value for α--the adjustment factor; then, this value can be used to produce an estimate for mean expenditure in the cost-sharing tier. By multiplying this value by the estimated number of observations in this tier obtained from a standard normal z-table, a precise budget impact estimate can be produced.

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