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Modelling Budget Impact: Analytical Techniques When Limits on Cost-Sharing are Imposed on Skewed Health Expenditure Data

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Abstract

Decision-makers often request costing models of multi-tiered benefit programs, such as those involving different levels of cost-sharing at each tier of expenditure. This situation presents particular modelling problems as health expenditure data available from related programs are likely to be positively skewed with non-constant variance. Based on the results of a Monte Carlo simulation producing 50 log-normal expenditure distributions, this paper provides a method for working with such data to produce cost estimates that utilize a composite measure referred to as the anchored distancea standardized measure of the range over which the tier is defined. This measure helps to determine a measure of central tendency of a tier equivalent to that of the tiers mean expenditure for the purposes of determining a unit price within each tier of a distribution of expenditures. The empirical results suggest that every one unit increase in the anchored distance results in a 26% shift to the left of the central tendency from the tiers median value. Further, this estimate is, on average, just 0.6% different from the actual mean price for the tier. This measure as well as that of a suggested measure of quantity are particularly useful as decision-makers vary the range over which cost-sharing is applied because they are simple to recalculate without requiring access to the complete expenditure data. This technique should assist economists who attempt to model statistically valid budget impact analyses using such data.

JEL Classification: I13
Keywords: expenditures; skewed data; budget impact; cost-sharing

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1 Background

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. (Bao, 2002; Bhattarai, 2014; Blough et al., 1999; Cantoni and Rochetti, 2006; Duan et al., 1983; Griswold, Parmigiani, Potosky, and Lipscomb, 2004; Jones, 2000; Manning, 1998; Matsaganis, Mitrakos, and Tsakloglou, 2009; Mullahy, 1998; Manning and Mullahy, 2001).

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 that have been largely undiscussed in the literature. One of these involves how to model budget impact analyses when the data exhibit such characteristics, and when the policy directive is to model expenditures when cost-sharing only applies to certain ranges of expenditures.

Budget impact analyses (BIA) estimate the financial impact of the adoption and diffusion of a new health intervention within a specific health care context (Mauskopf, 2007). Normally, BIA is straightforward. The multiplication of price or cost per unit by the quantity or number of people utilizing is the end product. However, the process of obtaining each of these components 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 exacerbated by skewed expenditure data. Often, these expenditure data are from a related program already in existence and serve as the basis for modelling the expected budget impact from a newly proposed program. This paper attempts to provide some analytical guidance for using such data in the context of modelling budget impact for various policy initiatives.

1.1 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. Often, these estimates will involve a portion of expenditures subject to a co-payment (i.e. between 2% and 3% of net income). The patient is expected to pay full cost until the lower limit (i.e. deductible) is attained; and beyond the upper limit–often considered a catastrophic threshold–the patient faces no out-of-pocket costs.

Many health insurance products in the United States 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.

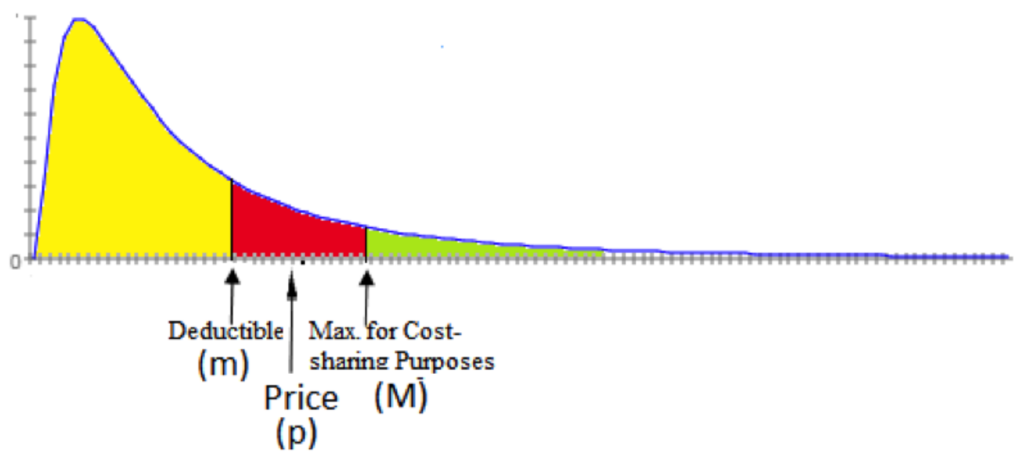

Figure 1: Hypothetical Skewed Health Expenditure Distribution with Three Tiers

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, the Trillium prescription drugs program in Ontario and many health insurance policies in the United States are catastrophic programs that have a per-service co-pay, rather than a range of expenditures over which cost-sharing applies. They are therefore considered two-tier insurance programs. This paper will mainly focus on modelling three-tier programs with some application to two-tier programs. The focus will be on obtaining both a representative measure of price or cost (P) for each tier and an associated measure of quantity or population size (Q) to be used in a budget impact analysis.

1.2 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. The 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 (Orlewska et al., 2009). 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 (Mauskopf, 2007); 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 (Lipscomb, 2009; Mauskopf, 2005).

Building on the ISPOR guidelines, this paper develops a new method for conducting BIA under cost-sharing arrangements with respect to the analytical policy issues described above (i.e. ranges over which deductibles and co-pays apply). A study interviewing key decision-makers in British Columbia shortly after their Fair Pharmacare policy prescription drug 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 (Morgan, 2006). This underscores the importance and practical application of carrying out statistically valid BIA when cost-sharing applies to a limited range of expenditures.

Additionally, an important policy issue related to the skewed data is better 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. While this paper does not develop a deeper understanding of these characteristics, it does provide improved methods for predicting government expenditures for higher-end utilizers when cost-sharing may be involved.

2 Methods

A Monte Carlo simulation was undertaken that generated 50 log-normal distributions of 20,000 observations each. These simulated distributions were designed to be reflective of potential expenditures for hypothesized insurance or health benefit packages for either overall health or for specific groups of health services. The distributions were modeled with a skew that is characteristic of log-normal distributions:

$$(e^{\theta^2} + 2)\sqrt{e^{\theta^2} - 1}$$

where θ represents the scale parameter or inputted standard deviation. One of the produced sample distributions is given below in Figure 2.

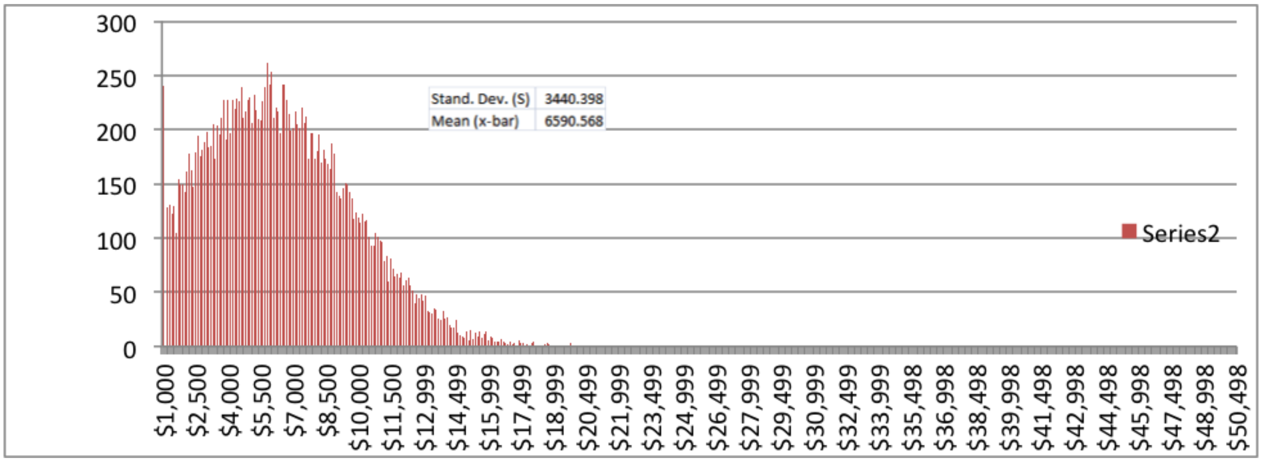

Figure 2: Sample Monte Carlo simulated distribution of health expenditures

There are also various general measures of skewness including the very intuitive Pearsons First and Second Moment Coefficients:

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

where μ is the arithmetic mean, ν is the median value, 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) utilized by major software packages like SPSS, SAS, Excel:

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

Which is equivalent to

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

where n is the sample size and xbar 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 (Doane and Seward, 2011). Bowing to this trend, this paper utilizes G_1 as an empirical measure of skewness.

When conducting the simulations, the inputted standard deviations ranged from \$3,000 to \$6,500. The 50 expenditure distributions generated from the Monte-Carlo process produced means with magnitudes in the range of \$6,425 to nearly \$9,000 with sample standard deviations, s, in the range of approximately \$3,200 to \$5,400. In applying the simulations, the outputted distributions were then divided into three tiers or segments into which a deductible, cost-share tier, and no cost-share tier could be assigned. The tier over which cost-sharing was modelled varied in terms of the standard deviations of the individual distributions with the lowest lower bound set at 0.3s above the mean and the highest upper bound at 2.3s above the mean.

Finally, the performance of the estimation method is tested by assessing the percent error difference between the estimated average price and the actual price obtained by averaging the values in the cost-sharing tier for each of the 50 simulated samples.

2.1 Determination of Price or Cost per Unit

The budget impact analyst must either calculate a mean expenditure (P) per unit of utilization (e.g., per person, or per family) for a particular expenditure tier or develop an alternative measure that is reliably close to the calculated mean. The paper aims to develop such an alternative measure for P specific to the cost-sharing tier so as to limit reliance on data center resources to recalculate such means every time the decision-maker requests changes in the size 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 an adjustment factor. The median 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:

$$P = m + (M - m)/\alpha$$

$$\alpha = (M - m)/(P - m)$$

To predict α, OLS linear regression techniques are utilized to regress α on G_1 of the designated tier or a highly correlated proxy associated with the range of the distribution associated with cost-sharing. Pearson correlation coefficients between G_1 of the cost-share tier and a selected proxy. We propose that the magnitude of the cost-sharing tier anchored by the mean of the entire distribution of expenditures that is referred to here as an "anchored distance" (Da) is a potential candidate proxy:

$$D_A = (M - m)/\mu$$

The motivation for using such a measure is that a larger range for a tier would naturally be associated with a larger value for the partial skew if the overall distribution is skewed. And much like the coefficient of variation - which is a standardized measure of dispersion, dividing by the overall mean provides a way to standardize the range over which a tier is defined.

The linear regression model to test for the association between the anchored distance and α is as follows:

$$a_i = \beta_0 + \beta_1 D_{Ai} + \epsilon$$

2.2 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 expenditure is illustrated below in Figure 3.

Log-normality can be roughly determined if the log-transformed data used to model program

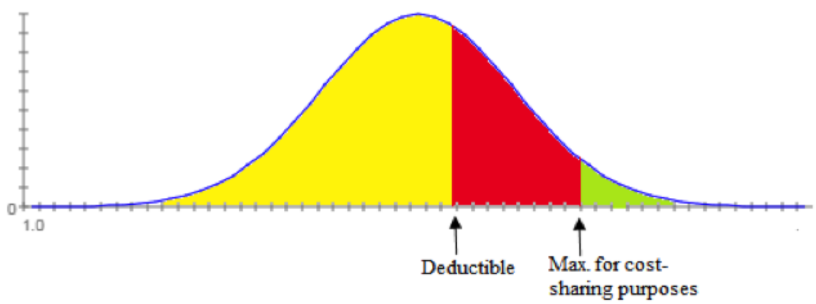

Figure 3: Hypothetical Transformed Log-Normal Health Expenditure Distribution with Three Tiers

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) 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 simulations were conducted using Excel 2010 (Excel, 2010) and STATA v. 12 (Statacorp, 2011).

3 Results

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

The summary data in Table 1 indicate that the calculated adjustment factor in these simulations varied from 2.03 (near the median value) to a maximum of 3.00 with an average adjustment for dividing the distance of the cost-sharing tier of 2.58. The various measures of skewness were all positive indicating a positive skew for all of the simulations even though the magnitude of these

Table 1: Descriptive Statistics

Variable	n	Mean (ln transform)	Standard Deviation	Minimum (ln transform)	Maximum (ln transform)
Adjustment factor (α)	50	2.58	0.17	2.03	3
Log-normal skew measure	50	1.42e+33	4.82e+33	2.65e+10	1.74e+34
Pearsons 2nd Moment Coefficient	50	0.31	0.09	0.05	0.47
G_1 measure of skew	50	0.59	0.06	0.49	0.73
G_1 (cost-sharing tier skew)	50	0.46	0.1	0.19	0.7
Anchored Distance (D_A)	50	0.7	0.21	0.2	1.06
Standard Deviation of Expenditures (θ)	50	\$3,764.41	\$554.61	\$3,239.10	\$5,363.74
Median of Expenditures (ν)	50	\$6,636.48	\$557.01	\$6,099.77	\$8,299.67
		(8.8)		(8.72)	(9.02)
Mean of Expenditures (μ)	50	\$7,045.20	\$668.26	\$6,425.62	\$8,999.87
		(8.86)		(8.77)	(9.1)
Coefficient of Variation	50	0.85	0.14	0.71	1.21
% error	50	0.56%	1.15%	0.035%	7.97%
% error (w/o outlier)	49	0.41%	0.38%	0.035%	1.73%

measures vary considerably from one another as there is no one correct skewness measure (Kenney and Keeping, 1951). The anchored distance (D_A) average 0.70 with a standard deviation of 0.21, a minimum of 0.20 and a maximum of 1.06 suggesting that these cost-sharing tiers are generally smaller in value than the average level of expenditures in each simulated distribution. The mean values for the untransformed data included those for the standard deviation of expenditures of over \$3,700 while the Median and Mean were approximately \$6,600 and \$7,000, respectively. The log-transformed data produced mean and median values that were within 0.1 of each other suggesting that log-normality was not an unreasonable assumption for these data. The coefficient of variation (θ/μ) - a standardized measure of data dispersion averages about 0.85 with a minimum of 0.71 and maximum of 1.21.

The estimator for the tier-specific average price was generally very precise with an average error from the actual average of just 0.56% with a single outlier that had an error of almost 8%. Without this outlier, the average error fell to just 0.41% with a maximum error of just 1.73% from the actual value.

Table 2: Pearson Correlation Statistics

	G_1 (cost-sharing tier skew)	Anchored Distance (DA)
G_1 (cost-sharing tier skew)	1.00***	0.85***
Anchored Distance (D_A)	0.85***	1.00***

***p $<$ 0.001

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

Table 3: OLS linear regression results (n =50)

Dependent Variable	Coefficient	Standard Error
Adjustment factor (a)		
Anchored Distance (DA)	0.69***	0.06
Constant (0)	2.09***	0.05

R-sqr (adj) = 0.71***
*p $<$ 0.05 **p $<$ 0.01, ***p $<$ 0.001

The OLS regression results in Table 3 suggest that any one unit increase in D_A is associated with 0.69 increase in the adjustment factor with the adjustment factor converging to 2 (the median) as $\lim_{M \to m} D_A = 0$.

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).

4 Discussion

The results of this simulation suggest that the analyst wishing to model the expected budget impact of a three tiered insurance policy utilizing skewed expenditure data can reliably - and relatively simply - do so utilizing the method 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 on a few summary statistics. A one unit increase in this measure is associated with a 0.7 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 a 26% [1- (2/(2+0.7))] shift to the left of the central tendency from the tiers median value. Performance of this estimator is quite precise with errors from actual tier prices averaging just 0.5%. When combined with the measure of Q obtained from ln-transformations of the endpoints and information contained in a standard-normal z-table, the analyst can produce a conceptually accurate measure of P*Q for any proposed budget impact analysis. 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 and then the analyst can proceed similarly with the methods outlined in this paper.

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 when conducting budget impact analyses for tiered benefit programs.

A limitation of these findings might be that the skew of the simulated distributions are not as highly skewed as most health expenditure distributions, such as those contained in the Medical Expenditure Panel Survey (MEPS) and health expenditures collected by health authorities in various jurisdictions around the world (Yu and Machlin, 2004). Further work might proceed to see if even more highly skewed distributions produce a similar relationship between α and D_A as calculated herein and reinforcing the validity of the findings. 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. 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 for other populations (Newhouse, 1993). 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 marketsfor example dental, prescription drugs, and vision care (Bhatti, 2007; Jin, 2012; Lurie, 1989). 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.

5 Conclusion

This simulation exercise represents a first attempt to provide the analyst with tools to undertake a budget impact analysis of a proposed three tiered cost-sharing health insurance program utilizing skewed expenditure data from a similar program elsewhere. 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 overall mean of the entire distribution, they can reliably predict the value for -the adjustment factor; this value, then can be used to produce a measure of central tendency for P in the cost-sharing tier of the expenditure distribution. The results suggest that there is utility using a measure referred to in this paper as the "anchored distance" to help determine a measure of central tendency for the different tiers of the expenditure distribution. Further work on more extensive simulations and actual data will help to further refine these techniques.

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