

A REVIEW: COSTS OF MENTAL HEALTH CARE DESCRIBED, DEFINED, OR PREDICTED BY REGRESSION MODELS

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ABSTRACT

An important vital part of research into the efficacy of mental health services is the study of the patterns of difference in health-care costs and the factors that affect them. To induce more thoughtful consideration of the precise objectives of these investigations and the selection of statistical techniques best suited to achieving them on the part of both the researchers of the variance in health care costs and the consumers of such studies. We give some examples of regression models that could be used to forecast the expenses of mental health care and explain how to pick the best one to utilise for a certain research project. This gap is to be filled by the current review. We neither intend to describe in-depth the instances in which each of these approaches has been utilised in the literature on mental health nor do we intend to evaluate the effectiveness of any specific usage. Given the inescapable space constraints of such a review, we won't linger on many of the technical specifics instead providing a brief overview of many of the current methods and highlighting how and when they might be useful. The analysis of incremental cost-effectiveness ratios using data from randomised controlled trials is a significant field of health economics that might not seem to have anything in do with health econometrics.

Keywords: Health Econometrics, Healthcare, Regression Model, Mental Healthcare.

INTRODUCTION

Defining the Goals of the Study

One of the most prominent observations observed after reading publications on the prediction of mental health costs is the common lack of clarity in the authors' goals, which is caused by the method in which they approach the idea of prediction. The term “*predictive power*” describes a model's capacity to distinguish across patients and take into account their varying costs. Sometimes authors are satisfied to only mention variations in the expenditures of medical care for various patient groups, typically presenting the outcomes of straightforward significance tests of group differences. Regression models are frequently employed in conjunction with this to “*explain*” or account for the cost variations within and between various patient categories. The ability to foresee or predict the costs of future patients is the final goal. Most of the time, authors don't distinguish between forecasting models and explanatory models, and as a result, they don't give much thought to which statistical approach or set of statistical techniques could be best for a certain aim. It is possible, and frequently likely, that authors have multiple connected goals in mind when presenting and analysing their data, but being more specific about what those goals are would be very beneficial for the reader (Amaddeo et al., 1998).

Distributional Properties of Cost Data

Cost data cannot be negative since they are almost always substantially positively skewed. The fact that the variance of the observations rises with their mean is another feature

of this type of data. Additionally, it is possible to experience censorship. In this case, data collection ends before some or all of the patients have incurred their complete health care expenditures. As a result, all that is known about the observed cost is that it represents the absolute least that a certain patient has paid for healthcare, but the precise amount is unknown. The issue of censorship is not specific to cost data. Readers will probably be more comfortable with it if it is used in the context of a timeline study of specific events. Examples of censoring include losing patients to follow-up before the data collection period is up or, if the cost of an illness episode is the variable of interest, ending the follow-up period before the patient's disease episode is over. Another scenario is the measurement of health care expenses being insufficient because the data file is missing one or two expenditures associated with a specific patient. Once more, we only know the minimum expense incurred for that patient. The present study does not cover censored data; instead, we direct interested readers to Diehr and to discussions of survival analysis (Barber & Thompson, 1998; Bonizzato et al., 2000).

Option of Regression Model

One of most efficient approach is to use multiple regression to directly model the observed cost. The fitting is carried out using the well-known ordinary least-squares methodology. The underlying multiple regression is that the impacts of the prediction factors are additive. Furthermore, when the error distribution has a non-constant variance, ordinary least squares are not the best fitting approach. In addition to invalidating model-fitting significance tests, these later data properties will also result in estimations of standard errors and confidence ranges for the parameter values. Ordinary least-squares modelling of raw cost data might also result in inaccurate cost estimates for some patients since it is based on false distributional assumptions. Therefore, it is not unusual that investigators may be motivated to employ techniques other than modelling of raw cost data (Byford et al., 2001).

Evaluation of the Model's Performance

To analyze the concordance between the expected and actual expenses in this case, we require an index or statistic. Note that the agreement between projected and observed log-costs is not, or should not be, of relevance to us. The standard Pearson product-moment correlation between expected and actual prices is perhaps the simplest index, but it is far from optimal. Using Lin's concordance coefficient or an intraclass correlation is generally preferable because it is a measure of association rather than concordance. But regardless of how accurately the forecasts were made, both of these indices—together with the product-moment correlation are dependent on patient heterogeneity; they will rise along with increases in cost variability (Hoch et al., 2002).

CONCLUSION

According to our and other people's experiences, a one-part model using ordinary least-squares on raw costs data routinely outperforms both the more theoretically sound log-linear generalised linear model and ordinary least-squares on logged costs in terms of performance. The former can occasionally result in inaccurate cost estimates, but this is not a major issue. In this regard, we proviso concur with Diehr and suggest using ordinary least-squares regression with raw costs. However, strategies that focus more on the costs data distribution or the use of strong model-fitting algorithms are likely to result in improvements over the use of conventional least squares. Analysts should seriously consider using a generalised linear model with a logarithmic link function and a suitably specified error distribution if they are primarily interested in explanatory modelling and believe that their

model should be multiplicative. The usage of two-part models, however, might have even more value as a tool for explanation. Bootstrapping is a highly helpful all-purpose and distribution-free way to get standard errors, confidence, and P values, but it shouldn't be used in place of carefully choosing the type of model to be fitted and the best model-fitting strategy to apply after that. Getting started comes later.

REFERENCES

- Amaddeo, F., Beecham, J., Bonizzato, P., Fenyo, A., Tansella, M., & Knapp, M. (1998). The costs of community-based psychiatric care for first-ever patients. A case register study. *Psychological Medicine*, 28(1), 173-183.
- Barber, J.A., & Thompson, S.G. (1998). Analysis and interpretation of cost data in randomised controlled trials: review of published studies. *Bmj*, 317(7167), 1195-1200.
- Bonizzato, P., Bisoffi, G., Amaddeo, F., Chisholm, D., & Tansella, M. (2000). Community-based mental health care: to what extent are service costs associated with clinical, social and service history variables?. *Psychological Medicine*, 30(5), 1205-1215.
- Byford, S., Barber, J. A., Fiander, M., Marshall, S., & Green, J. (2001). Factors that influence the cost of caring for patients with severe psychotic illness: Report from the UK700 trial. *The British Journal of Psychiatry*, 178(5), 441-447.
- Hoch, J.S., Briggs, A.H., & Willan, A.R. (2002). Something old, something new, something borrowed, something blue: a framework for the marriage of health econometrics and cost-effectiveness analysis. *Health Economics*, 11(5), 415-430.

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