CHSR Center for Health Services Research
Applying Research to Optimize Care©

What We Are Reading

Synopses of recent studies in health services research
Volume 3, Issue 1a

Using Length of Stay to Control for Unobserved Heterogeneity When Estimating Treatment Effect of Hospital Cost with Observational Data: Issues of Reliability, Robustness, and Usefulness

Take Away Points

- Observational studies evaluating the effect of interventions (e.g., targeted quality improvement efforts to improve care) in the hospital often use length of stay (LOS) as a variable to control for unobserved heterogeneity in determining the intervention's (i.e., treatment's) effect on costs.
- Both the magnitude and significance of results varied widely depending on the method used to control for LOS.
- Use of LOS as a control suffers from endogeneity and bias
  - LOS may be highly correlated with both costs (outcome) and treatment (more complex patients stay longer) undermining estimation of the causal relationship.
- Multiple sensitivity analyses with and without length of stay controls should be reported when estimating an intervention's effect on hospital cost.
- To minimize endogeneity and maximize validity, researchers should match and analyze treatment and comparison groups on baseline factors only. Incorporation of the timing of an intervention during a hospitalization in the analysis may yield more reliable, more robust and more useful results than using LOS controls.

The Issue

Source
May P, Garrido MM, Cassel JB, Morrison RS, Norman C. Using Length of Stay to Control for Unobserved Heterogeneity When Estimating Treatment Effect of Hospital Cost with Observational Data: Issues of Reliability, Robustness, and Usefulness. *Health Services Research*. Oct 2016, 51(5):2020-2043. http://onlinelibrary.wiley.com.ezproxy.uky.edu/doi/10.1111/1475-6773.12460/epdf

While randomized controlled trials are the strongest way to evaluate the causal effect of interventions, randomizing patients to receive interventions is often not possible. Thus, health services researchers must use observational study designs, particularly when attempting to answer questions regarding treatment effect on cost. The major difficulty in observational analyses is determining whether differences in outcomes between the intervention versus control group are due to the intervention or from confounders—observed and/or unobserved. Researchers can control for observed confounders using statistical matching techniques such as propensity scoring. Accounting for unobserved heterogeneity poses a great concern for researchers seeking to infer casual effects using observational data. This challenge is magnified when examining treatment effects on healthcare utilization (e.g. costs, readmissions), because the distribution of utilization outcomes can be skewed by a minority of complex patients. Of note, complex patients can distort treatment effect estimates even in the absence of confounding, and clinical complexity cannot easily be captured adequately through administrative or interview data. Despite these issues, multiple hospital studies evaluating the causal effect of an intervention on utilization have used LOS as a proxy for clinical complexity and a controlling variable in analyses using 3 approaches:

1) LOS as a covariate – predictor in the regression to estimate treatment effect on cost
2) LOS as a sample parameter – short- and/or long-stay outliers removed from the sample *ex ante*
3) LOS as an outcome denominator – average daily costs as outcome (total costs/LOS)

The purpose of this study was to evaluate and compare the sensitivity of estimates of a treatment's impact on hospital costs to methods of controlling for LOS and identify strengths and weaknesses of each method.

Study Methods and Design

Data for this study was drawn from a prospective, observational study on the effect of palliative care consultation team (PCCT) interventions for hospitalized patients with advanced cancer. Data collection included descriptive, clinical, and utilization data on patients admitted to four of five hospitals participating in the Palliative Care for Cancer (PC4C) study. The fifth hospital was excluded because cost data was not collected. Clinical data was abstracted from medical record review and patient interviews. Cost data were extracted from hospital databases, adjusted for regional variation, and standardized to US dollars in 2011 (the final year of data collection).

The primary sample included 969 patients used in the propensity score-weighted samples. When the sample was trimmed due to LOS, new sample-specific propensity scores were created by discarding all observations outside the sample's LOS range and then repeating the weighting process for the remaining treatment and comparison group patients. The primary outcome was total direct costs incurred by the hospital for the hospitalization. The primary independent variable was a binary treatment variable: "Did patients receive a consultation from the PCCT during their hospital admission?" All regressions were performed against the treatment variable and propensity score variable plus fixed effects for each hospital site.

Analysis

Costs were modeled using generalized linear models (GLM). Mean incremental effect of PCCT on total direct hospital costs was calculated, and sensitivity analyses were conducted.

Length of Stay Controls

LOS as a covariate is linearly correlated with total cost of hospital stay. Therefore, cost was estimated using nonlinear transformations of LOS as a covariate. The base model [Model (i)] included main effects for the treatment variable and the observed covariates in the propensity score, fixed effects for sites, and error terms. Models (ii), (iii), and (iv) included LOS to the second, third, and fourth power. Model (v) included a log-transformed LOS term.

For this study, the sample was trimmed of short-stay patients at the 5th percentile; of long-stay patients at the 95th percentile; and of both simultaneously at the 2.5th percentile and 97.5th percentiles. These parameters were set to maximize sample size in investigating the impact of defining the sample by LOS. For each subsample, Models (i) and (v) were rerun and estimated mean incremental treatment effects. The researchers evaluated LOS as an outcome denominator using regressions with average daily direct costs (the ratio of total hospital costs to LOS) as the outcome of interest for the sample population and the 3 trimmed subsamples. These were calculated using only Model (i) as LOS is included in the regression as the outcome of interest.

Key Findings

- ***LOS as a covariate*:**
  - In the principal sample, Model (i) showed a negligible association between treatment and costs $153 (95% CI: -1,266 to 1,572) or 1.6% increase in total direct hospital costs for patients who received PCCT.
  - Trimmed subpopulations for short-stay patients and combined short- and long-stay patients resulted in nonsignificant estimates in Model (i) compared to statistically significant cost

savings with Models (ii) and (v) in the $980-$1,617 range or 10-17% cost-saving from the intervention.
    - The trimmed long-stay patient subpopulation consistently resulted in statistically significant cost-saving association between all models ranging from $1,141 to $1,609 or a 41% difference in cost savings.
- ***LOS as a sample parameter***:
    - Estimated treatment effect was negligible for the principal sample and was not statistically significant when trimming short-stay patients or combined short- and long-stay patients.
    - The trimmed long-stay patient subpopulation resulted in statistically significant mean cost-saving effect of -$1,141 (95% CI: -1983 to -299; p=.008) or 12% reduction in total direct hospital cost per case.
- ***LOS as an outcome denominator***:
    - The estimated treatment effects on average daily direct cots suggest a statistically significant cost-savings effect irrespective of sample or subpopulation in the range $110-174 or a 58% difference in estimates.
    - The estimated effects on means daily costs are equivalent to 9-13% reductions which are slightly lower than the equivalent estimated savings where LOS was used as a covariate.
- Early palliative care was associated with a significant cost-saving effect and this effect is larger when treatment is received earlier
    - Intervention timing contributed to understanding the inconsistency in results using LOS controls (i.e., long-staying patients have later consults)

Limitations

- LOS as an outcome denominator is difficult to interpret if LOS differs between the treatment and comparison group, which is the case in this study.
- This a single study and the results need to be replicated in other empirical datasets.
- There may be unobserved baseline heterogeneity between treatment and comparison patients that is unconnected to LOS and treatment timing which has been unaccounted for in this analysis.

Final Thoughts

When assessing issues of reliability, robustness and usefulness of using LOS controls to determine treatment effect on hospital cost, health services researchers should be cognizant of the potential strengths and weaknesses of each method. The authors recommend that researchers match and analyze treatment and comparison groups on baseline factors only. Furthermore, the authors indicate that including time to intervention in the model can produce more reliable, robust, and useful results than using LOS controls. Moreover, continued efforts should be made to develop more reliable and robust methodologies that reduce unobserved heterogeneity when using observational data to evaluate treatment effect on hospital cost to generate more useful results.