CRITICAL CARE USE DURING THE COURSE OF SERIOUS ILLNESS

Online Methods Supplement

by

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Cohort Construction

The Care after the Onset of Serious Illness (COSI) dataset was analyzed; this is a dataset built based on Medicare claims. Medicare data capture 96% of the American population older than 65 (E1). COSI contains clinical, demographic, and other information about a population-based cohort of 1,164,790 elderly patients identified at the time of initial diagnosis with a serious illness in 1993. In the first stage of data development, a cohort of all patients *newly* diagnosed with one of the following diseases were identified: cancer of the lung, colon, pancreas, urinary tract, liver or biliary tract, head or neck, or central nervous system, as well as leukemia or lymphoma, stroke, congestive heart failure (C.H.F.), hip fracture, or myocardial infarction (M.I.). These diseases were chosen to represent diverse, common illnesses that account for the majority of deaths in the U.S.; we also required that these illnesses have an onset date that could be reliably determined from Medicare claims (E2). Illness onset date was operationalized as first hospitalization with malignancy or CHF (E3, E4); it was operationalized as hospitalization for MI, stroke, or hip fracture if those diagnoses were designated the primary diagnosis, as others have done (E5-7).

For inclusion in the COSI sample patients had to be at least 68 in order to allow three prior years of claims to be examined so as to reliably exclude prevalent cases (E3, E4). Moreover, patients had to reside in the 50 United States or the District of Columbia and have valid claims data (including complete age, sex, ZIP code, admission date and discharge date) in order to allow accurate ascertainment of eligibility.

Patients in COSI were followed through the end of 1997, by which point nearly 65% had died. All critical care use in the U.S., as recorded in the Medicare claims, could then be examined. Patients were empanelled based exclusively on their claims up to cohort inception, without reference to any future outcome or use of medical care.

For the purposes of the current project, we required that the individual have been initially hospitalized at a hospital that could be linked to the American Hospital Association survey data and have a valid county identifier in the claims; 1,108,060 patients (95.1%) met these criteria.

This research was approved by the University of Chicago Institutional Review Board.

Covariate Definitions

All other diseases that patients may have had beyond their primary diagnosis (for example, as noted on prior hospitalizations for other conditions) were collected and treated as co-morbidities using an implementation of the Charlson score (E8-10). Medicare data have certain well-known limitations with respect to their racial classification system, and the race codes provided in the claims can only be reliably used for White/non-White comparisons (E11, E12). However, with access to the names of beneficiaries, it is possible to apply large-scale, well-validated computerized algorithms for identifying Hispanic and Asian-American ethnicities, substantially improving the adequacy of the racial/ethnic classification system (E13, E14). The Asian-American surname algorithm was developed among those born before 1941 and alive in 1990 who have applied for Social Security; using a gold standard of country in which the person was born (for this relatively new immigrant population), the algorithm has a positive predictive value of 0.82 for the groups included. The Hispanic surname algorithm was developed using Hispanic self-identification in the 1990 Census as the gold standard in all age groups; it has a positive predictive value of 0.93. Throughout this manuscript "White" and "Black" refer to non-Hispanic White and non-Hispanic Black; the shorter words are used for expositional convenience. Medicaid receipt, an individual-level proxy for poverty status, was obtained directly from the Denominator File, as is conventional (E15-22). We also linked individuals at the ZIP-code level to 1990 Decennial Census median incomes (ZIP codes aggregate 25,000 – 50,000 people). This provides a continuous measure that is likely well-correlated with total household financial resources. This approach has been validated (E23, E24) but has certain important limitations (E25-27); in particular, we must avoid interpretations of these area-level coefficients as directly representing the effects of changes in household income.

Statistical Methods

We use a variety of different approaches to summarize the diverse distribution of outcome variables present in the study: full distribution curves, counts of use, and, for clarity, dichotomization into "no use" vs. "any use" (E28, E29). T-tests are used for comparing continuous variables, χ^2 tests for categorical variables. Logistic regression is used for multivariable adjustment; 95% confidence intervals are presented. Because of the sample size, results of little meaningful difference could easily be statistically significant; therefore comparison values are presented as appropriate. Kaplan-Meier curves were used to evaluate the impact of differential mortality by age and other demographics factors on the results of logistic regression; as no difference in interpretations arose, the logistic regressions are presented for ease of interpretation in the print article.

Sensitivity Analysis of Findings on Age-Gradient in Critical Care Use.

Figure E1 shows a Kaplan-Meier curve of time from diagnosis until critical care use among patients who did not use critical care during their index admission, stratified by age at diagnosis. For clarity, three age strata are shown. Patients are treated as censored upon their death. This demonstrates that the age gradient in critical care use is not an artifact caused by simply the higher mortality of older seriously ill patients. Not only are older patients less likely to use critical care at any point, in an “age-dose”-dependent manner; this is demonstrated by the fact that the curves for older patients are always above the curves for the lower patients. Also, at any given point, the slope of the curves for the younger patients is steeper – that is, among those still alive at any given X days after diagnosis who have not yet used critical care, younger patients are always more likely to use critical care during the next period.

Online Supplement References

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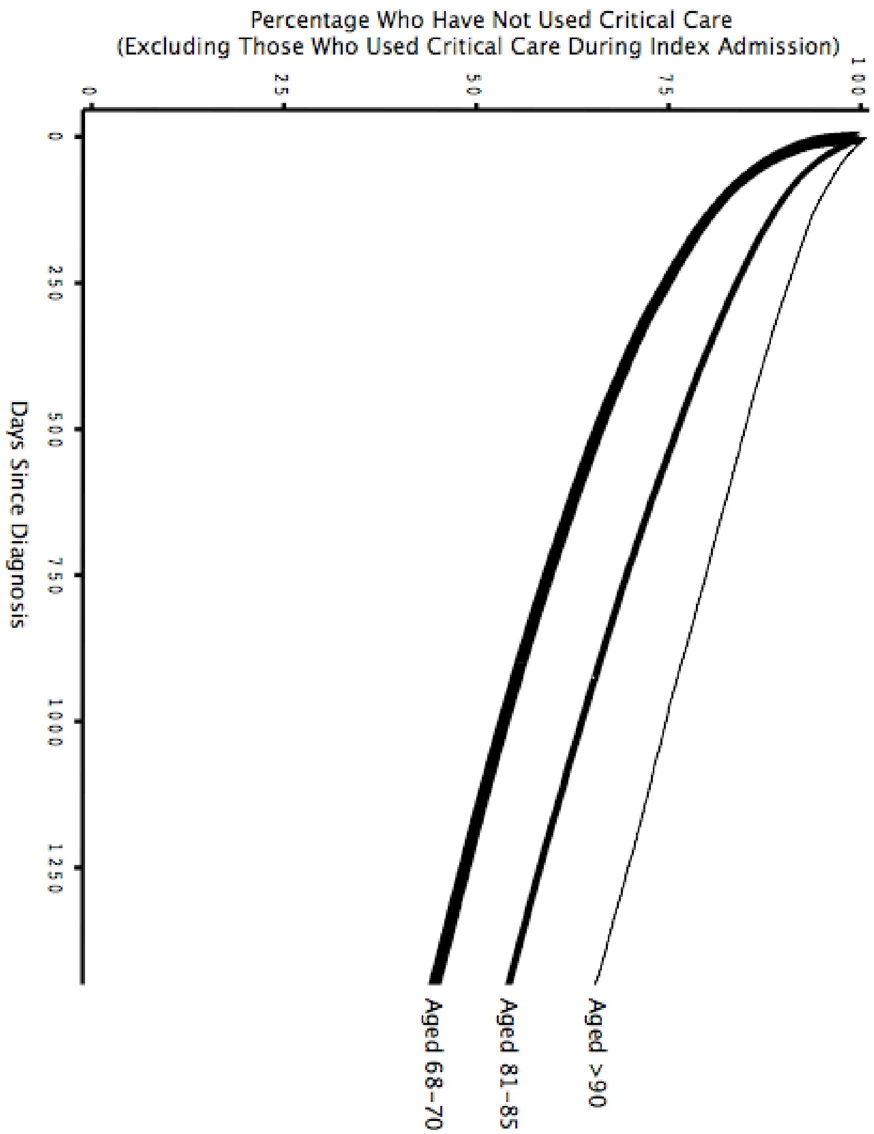
Online Supplement Figure Legend

These Kaplan-Meier curves show time from diagnosis until critical care use. Patients who used critical care during their index admission are excluded. Patients are censored at time of death. Note that these restrictions make these curves only interpretable in the context of a sensitivity analysis.

Figure E1:


Percentage Who Have Not Used Critical Care
(Excluding Those Who Used Critical Care During Index Admission)
0
25
50
75
100
Days Since Diagnosis
0
250
500
750
1000
1250
Aged 68–70
Aged 81–85
Aged >90