Rural hospitals in financial distress: The ethics of holding hospitals in underserved communities to capitalist standards

Razmin Bari

11/12/24

Introduction

Rural hospitals in the United States are responsible for the healthcare needs of a particularly under-served portion of the population to whom other healthcare facilities may not be within feasible distances. Unfortunately, they have been at increasing risk of closure over the past few decades. Negative profit margins have been hypothesized to be the reason, and so researchers at the North Carolina Rural Health Research Program have been putting in considerable efforts to develop a model that can reliably predict whether a rural hospital will fall into financial distress (Malone et al.). Ideally, the model proposed in the article titled "An updated model of rural hospital financial distress" would flag the hospitals at high risk of closure within the next two years, which would then allow concerned authorities to bring forth relevant interventions such as increased funding.

The first part of this final project will recreate the statistical analysis done in the aforementioned paper (the code for which is currently not publicly available) using a slimmed version of the paper's analytic dataset[1]. This part also includes simulations to compare how the model performs on similar datasets. The second part of the paper will analyze the normative concerns that may rise from using such a model in real-world settings, and debate whether the methods used inherently counter some of the concerns.

[1] Analysis of Methods

Data

The dataset I utilize here is a de-identified version of the dataset used in the paper's original analysis. It includes the following covariates that can be divided into four sub-domains:

(A) financial performance: (1) hospital profitability, (2) uncompensated care, (3) outpatient revenue and CAHMPAS score (a performance metric based on benchmarks set by Critical Access Hospital Measurement and Performance Assessment System),

(B) government reimbursement: (4) Critical Access Hospital (CAH) status, (5) Medicare outpatient payer mix expressed as a percentage of all outpatient charges, (6) ratio of Medicare Advantage and cost plan days to traditional Medicare acute care days, (7) Medicaid-to-Medicare fee index, and (8) Medicaid payer mix expressed as a percentage of all patient charges,

(C) organizational traits: (9) ownership, and (10) system affiliation,

(D) market characteristics: (11) competition

The original analytic dataset included four more variables that the researchers do not wish to disclose publicly at this time. Hence, any coefficients calculated going forward will not be the same as the original analysis, but should still yield comparable results.

[1] obtained via direct correspondence with the first author, Dr. Tyler L. Malone

Three binary financial distress outcomes were chosen for consideration: negative cash flow margin (a profitability metric), negative equity and hospital closure. This data set consists of 46200 observations owing to its 'stacked' nature: there are multiple rows for each hospital-year (one row for each combination of hospital, year, and type of financial distress outcome). Rows with any missing data is removed and so, the complete case analysis was conducted on 42226 observations.

Recreating original probit regression analysis

The probit regression model was specified as follows:

Financial distress indicator $= \beta_0 + \sum_{i=1}^{p} \beta_i * X_i + \epsilon$

where β_0 is the intercept, β_i are the coefficients for the predictors X_i, and ϵ is the error term.

Maintaining the paper's decision to not report the uninterpretable probit coefficients, here are the statistically significant Average Marginal Effects (AMEs) given a one standard deviation change in the covariates, along with corresponding p-values:

Table 1: Average Marginal Effects for Financial Distress Model

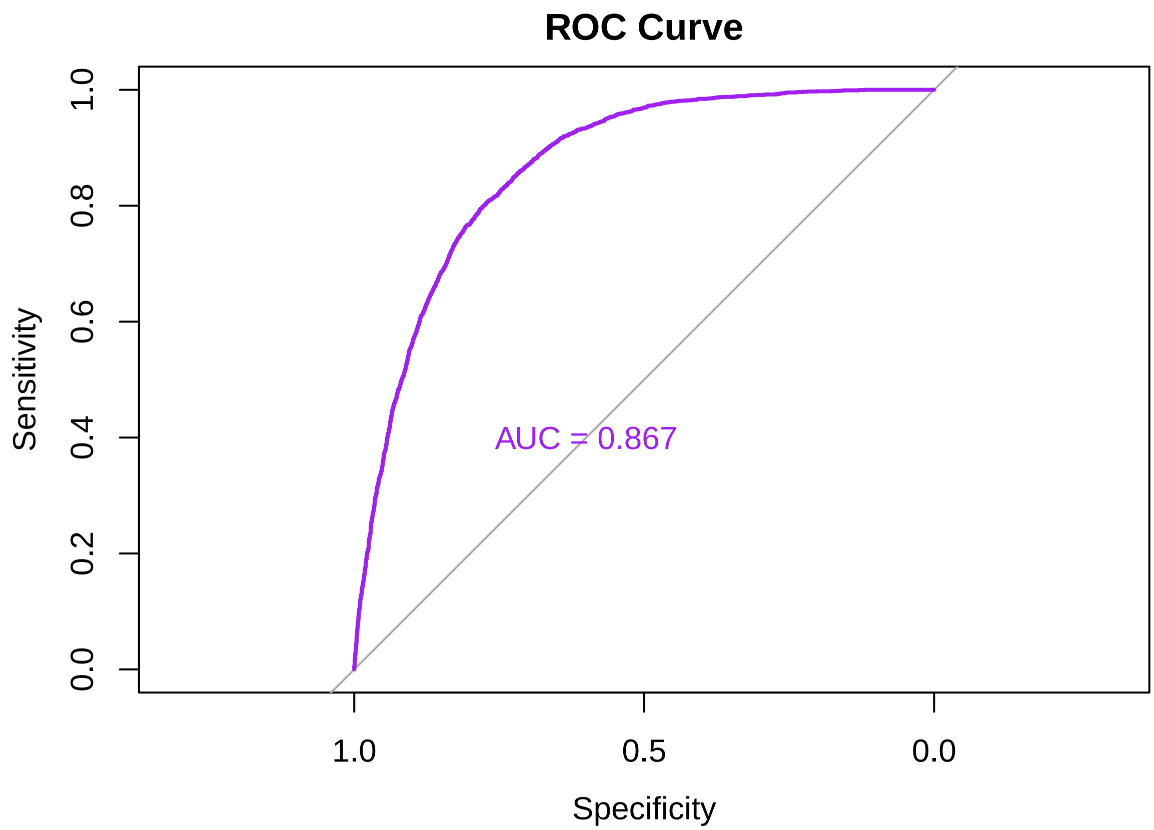
	Description	Variable	Average marginal effect	Standard error	p-value
1	CAH indicator variable	cah_indicator	0.01682	0.00330	0.00000
2	/Negative Cash Flow Margin/	financial_distress_typeNegative cash flow margin	0.21768	0.00333	0.00000
3	/Negative Equity/	financial_distress_ equity	0.09464	0.00249	0.00000
4	For-profit indicator	forprofit_indicator	0.04246	0.00448	0.00000
9	Percent Medicare outpatient payer mix	medicare_payer_n	-0.00862	0.00167	0.00000
10	Percent outpatient to total revenue	outpatient_to_total_revenue	-0.01343	0.00139	0.00000
11	Percent CAHMPAS benchmarks met (2 years)	pct_cahmpas_ben	-0.04552	0.00185	0.00000

12	System affiliation	system_affiliation_indicator	0.00667	0.00304	0.02798
13	Percent total margin, year t	total_margin	-0.02507	0.00177	0.00000
14	Percent total margin, year t - 1	total_margin_tminus1	-0.00632	0.00186	0.00067
15	Percent total margin, year t - 2	total_margin_tmi	-0.01690	0.00164	0.00000
16	Uncompensated care as a percentage of operating expenses	uncompensated_care	0.01316	0.00128	0.00000

To clarify with an example, an increase of one standard deviation in uncompensated care as a percentage of operating expenses increases the probability of future financial distress by 1.3%

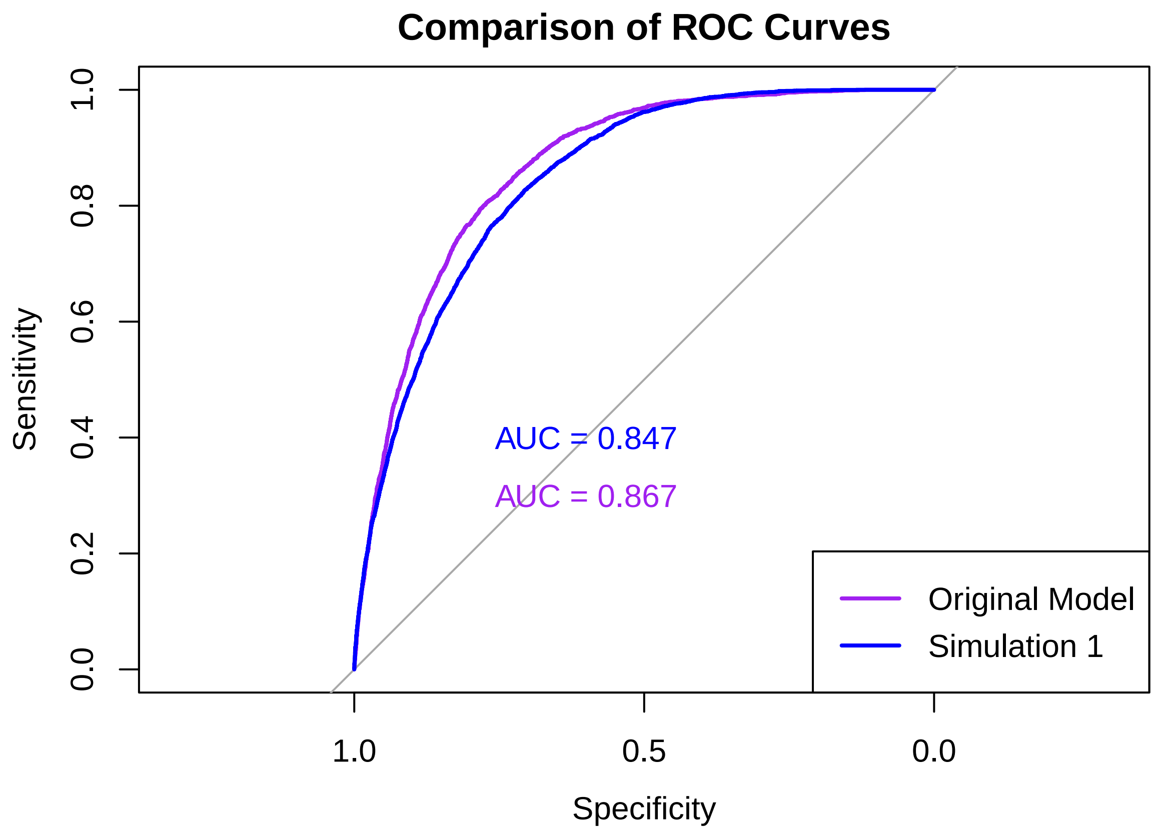
The stacked nature of the dataset has allowed the model to be optimally parsimonious. It also increased the risk of multicollinearity. Hence, the Variance Inflation Factor (VIF) was calculated, and no predictors had high VIF values, suggesting that multicollinearity among covariates is not a significant concern for the model.

To evaluate the model's performance, the area under the receiver operating characteristic (ROC) curve (AUC) was computed for the test dataset. The AUC value of 0.867 indicates strong predictive power for the model. The following ROC curve was plotted to visually assess the trade-off between sensitivity and specificity at various thresholds:



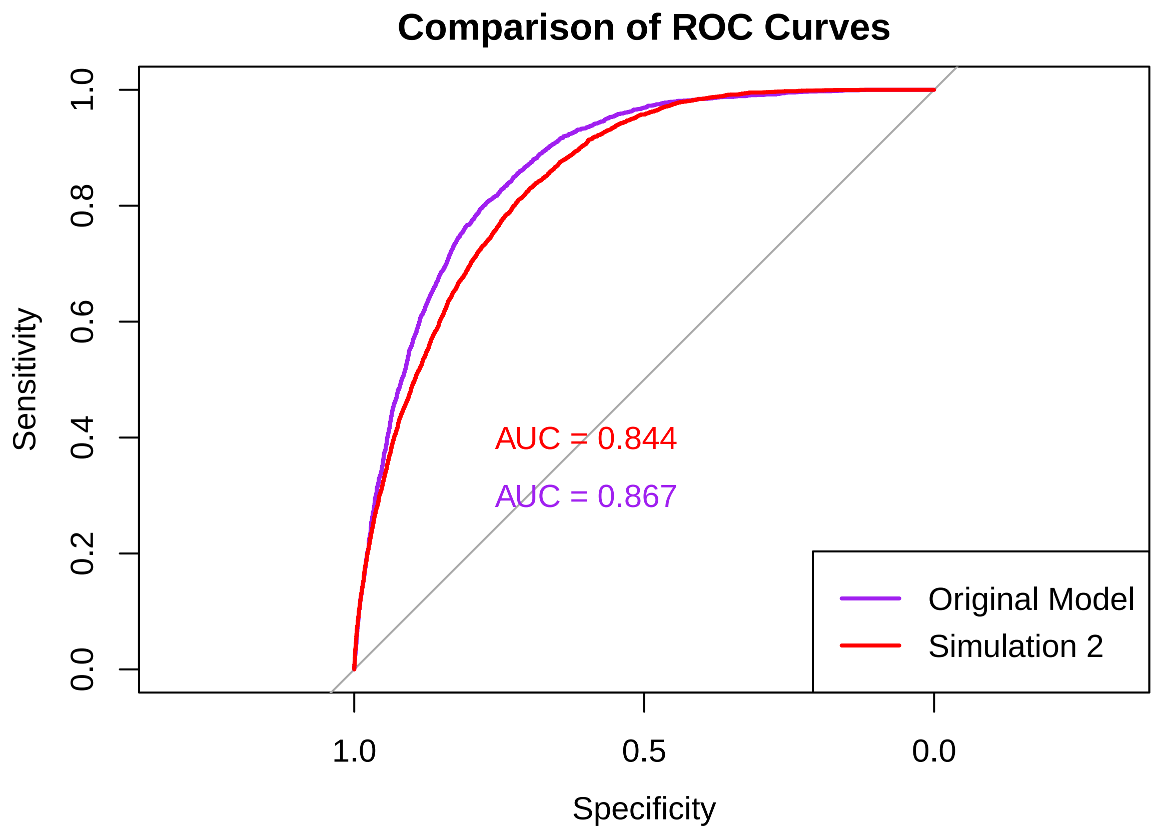
Simulation Study

To assess the robustness of the model, I simulated a dataset resembling the original data by sampling from the continuous variables' means and covariance structure, and simulating binary and categorical variables based on their observed proportions in the dataset. The simulated dataset was used to fit the same probit model. The model was then evaluated on this simulated data, and the confusion matrix revealed a classification accuracy of 89.2%. The AUC for the simulated data was 0.847, showing comparable but slightly reduced model performance. The ROC curves for both the simulated and original data are below:



Sensitivity Analysis: Modifying Proportion of Negative Profit Margin

In a further analysis, I simulated a scenario where the proportion of hospitals with a negative total margin was increased to 60%. The probit model was refitted to this modified dataset, and the confusion matrix revealed that the classification accuracy of 89.2% was maintained. The ROC curve comparison showed a slight reduction in model performance (AUC = 0.844) compared to the original model, as presented below:



[2] Analysis of Normative Consideration

Ideally, this predictive model would serve as a decision-making tool to identify hospitals at risk of financial distress, potentially increasing funding or driving policy changes to support these institutions. However, a critical limitation of this approach is its failure to account for the possibility of (reverse) causation among the covariates and the financial distress outcomes. For instance, a hospital's negative cash flow margin—representing low profitability—could itself be the cause of certain covariate values, such as high uncompensated care or low outpatient revenue. In such cases, the model might simply be reflecting symptoms of financial distress rather than identifying the root causes. If profitability becomes the primary determinant for funding or intervention based on the model's predictions, a hospital's ability to demonstrate financial health may unjustly dictate whether it receives the support necessary to remain operational.

This concern is particularly salient given that one of the statistically significant predictors in the Malone et al. study was percent total margin, often used as a proxy for profitability. Indeed, three measures of percent total margin are included, including values from up to two years ago for a given observation. In my own analysis above, an increase of one standard deviation in percent total margin showed a statistically significant decrease in the probability of future financial distress by about 2.5%. It is worthwhile to note that the model's predictive accuracy does not degrade when the proportion of hospitals with negative profit margins was increased in the simulation study. This shows that the model is not as heavily swayed by variables of profitability as one might think. On the other hand, the decrease in AUC does suggest some loss of predictive power which requires further analysis to be sure that inequities are not exacerbated.

Regardless, employing such a model raises profound ethical concerns. From a consequentialist perspective, the ethical evaluation of an action is based on its outcomes. Consequentialists argue that an action is morally right if it leads to the greatest good for the greatest number of people. Employing a model that prioritizes the monetary interests of hospital owners over the well-being of the community fails this test. By allowing financial metrics to dictate intervention decisions, such an approach could lead to the closure of hospitals that are vital to underserved communities, resulting in widespread suffering and reduced access to healthcare. The negative consequences for large rural populations far outweigh any benefits accrued by a small group of stakeholders.

For deontologists, morality is determined by adherence to the inherent dignity of moral agents. Deontologists would critique this model for its instrumentalization of patients, reducing them to mere means to lead to the end that is hospital profitability. Regardless of geographic or economic circumstances, patients have an inalienable right to proper healthcare. A system that subordinates this right to financial considerations breaches the categorical imperative to treat individuals as ends in themselves.

Virtue ethicists evaluate actions based on the character and virtues of the decision-makers involved. This ethical framework emphasizes cultivating virtues such as compassion, justice, and beneficence. A model that prioritizes corporate greed over the moral imperative to care for vulnerable patients reflects a failure to embody these virtues. It is inconsistent with the character of a compassionate healthcare provider, whose duty is to prioritize alleviating suffering and promoting well-being. From this perspective, a profit-driven approach undermines the moral integrity of healthcare systems, as it replaces virtuous motivations with self-serving goals.

Conclusion

By prioritizing profitability as a criterion for allocating resources, the model outlined in the chosen paper risks reinforcing systemic inequities. For rural hospitals serving economically disadvantaged populations, low profitability often stems from structural factors like high poverty rates or inadequate insurance coverage among patients.

My recreation of the statistical analysis as well as my analysis of ethical concerns highlights an issue becomes even more urgent in the current climate, where rural hospitals face growing financial pressures and are at risk of closure. The collapse of these institutions leaves rural communities increasingly vulnerable to complete healthcare inaccessibility. Consequently, it is imperative that any predictive model used to guide policy decisions on rural hospitals moves beyond profit-maximization metrics. Instead, models should incorporate community-centered measures, ensuring that funding and interventions align with the healthcare needs of underserved populations. Policymakers must approach rural healthcare with an ethical framework that prioritizes equitable access and the intrinsic value of human life over market-driven outcomes.

References

1. Malone, Tyler L, et al. "An Updated Model of Rural Hospital Financial Distress." The Journal of Rural Health, 3 Oct. 2024, https://doi.org/10.1111/jrh.12882.