


Measuring the COVID-19 Financial Threat to Hospital Markets

Anthony W. Orlando, MSc, PhD¹ , and Robert I. Field, JD, MPH, PhD^{2,3}

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Abstract

Many hospitals have been straining under the financial stress of treating COVID-19 patients. Those experiencing the greatest strain are in markets burdened with high levels of debt and uncompensated care. We propose a new measure of financial risk in a hospital market, combining both pre-existing financial vulnerability and COVID-19 severity. It reveals the highest concentrations of risk in counties with high poverty, low population density, and high shares of foreign-born and non-White populations. The CARES Act Provider Relief Fund helped many of the hospitals in these regions, but it left many markets with the same overall vulnerability to financial strain from the next health crisis.

Keywords

COVID-19, hospital finance, medical debt, hospital closure, healthcare access, CARES Act

What Do We Already Know About This Topic?

It is known that, before the COVID-19 pandemic, many hospitals were operating with slim financial margins. Throughout the pandemic, those in some regions lost significant amounts of revenue from cancellation or postponement of elective procedures to devote capacity to COVID-19 care.

How Does Your Research Contribute to the Field?

Our study creates the first measure of financial risk in hospital markets, which we considered on a county-by-county basis. It combines indicators of pre-pandemic financial vulnerability and the local severity of COVID-19. While it does not measure the vulnerability of individual hospitals, it indicates which markets are at highest risk of hospital financial distress and closures that could impair healthcare access for residents.

What Are Your Research's Implications Toward Theory, Practice, or Policy?

Our model indicates that hospital markets faced greater financial risk from this combination of factors in rural counties with economically disadvantaged households and in counties with larger proportions of vulnerable minorities. While federal financial support has been largely targeted toward those counties having greater hospital financial risk, many counties have not received aid proportional to their level of risk.

¹Finance, Real Estate, & Law, College of Business Administration, California State Polytechnic University, Pomona, CA, USA

²Law, Kline School of Law, Drexel University, Philadelphia, PA, USA

³Health Management Policy, Dornsife School of Public Health, Philadelphia, PA, USA

Corresponding Author:

Anthony W. Orlando, Finance, Real Estate, & Law Department, College of Business Administration, California State Polytechnic University, Pomona, 3801 West Temple Avenue, Pomona, CA 91768, USA.
Email: aworlando@cpp.edu



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Introduction

The financial stress on hospitals resulting from the COVID-19 pandemic has been widely noted.¹ Nationwide, most have had to reduce or eliminate some or all profitable elective procedures, while facing substantial new expenses for personal protective equipment.² The financial stress has been particularly acute for hospitals in rural areas. A disproportionate share of residents of these areas has risk factors for severe COVID-19 infections, and hospitals in them already tended to be in more precarious financial condition than their urban counterparts (Kaufman, Whitaker, Pink, and Homes, 2020; Khullar, Bond, and Scherpo, 2020).^{3,4}

Population risk for severe COVID-19 infections and pre-existing hospital financial vulnerability are each significant stressors by themselves, but when they coincide, their effects can be magnified. A combination of them would present the clearest estimation of the level of financial risk for a hospital market. We propose a methodology for doing so to create a single index, and we apply it to classify hospital markets into 4 categories of risk, as represented in Figure 1.

This new index expands the dimensions and determinants of financial risk in hospital markets, showing where the risk has been heightened by the surge of COVID-19 patients. Previous studies have either identified health conditions that make populations more susceptible to COVID-19—therefore imposing a greater stress on hospital capacities—or examined the financial sustainability of individual hospitals.⁵⁻⁷ This research focuses on hospital markets, where populations and hospitals interact, to create a combination of these 2 dimensions that can be used to compare financial stress across all geographies, not just rural areas where most prior research has focused. While this analysis does not explore the important heterogeneity across hospitals that exist *within* counties, our county-level approach allows it to be replicated with publicly available data for real-time decision-making.

Data and Methods

Our analysis uses data that are publicly available at the county level to compile 2 series of variables to measure the financial

vulnerability of hospitals in a market resulting from the COVID-19 pandemic: COVID-19 severity and hospital financial vulnerability. To assess COVID-19 severity, our series includes 4 variables. The first 2, cumulative infection cases per 1000 residents and cumulative attributable deaths per 1000 residents, were obtained from the *New York Times* database as of June 8, 2021. (Data are available for download at <https://github.com/nytimes/covid-19-data>). Another potential variable, hospitalizations, is less easily available to the public at the county level. To ensure that our method is not missing significant variation, we downloaded *state*-level hospitalization data from the University of Minnesota COVID-19 Hospitalization Tracking Project, and we regressed it on state-level cases and deaths. These 2 variables explain over 90% of the variation in hospitalizations, confirming that this third variable would not add much variation to our Index. The third variable, high-risk share of the county's population, is a joint product of the Dartmouth Atlas Project, CareJourney, and Microsoft Healthcare NeXT, which use Medicare claims data to measure the percentage of the population that is at least 65 years old and has at least 2 chronic diseases. (Data are available for download at <https://www.dartmouthatlas.org/covid-19/>.) The fourth variable, non-White share of the population, was estimated using U.S. Census data for 2019 (The 2020 Census data are not yet available for all of these variables). Multiple regression analysis indicates strong correlations among these variables (see Figure 2). For example, each infection case is positively associated with .011 deaths ($P = .000$), and a 1 percentage point increase in the share of high-risk residents is associated with 15.979 more deaths per 1000 residents ($P = .000$). The full set of pairwise correlations is reported in Table 1. Of the 6 pairs of variables, 5 are statistically significant at the .1% level. These correlations support their combination into a single factor for COVID severity.

To measure the overall financial vulnerability of hospitals in a market, our series includes 6 variables. The first, acute care beds per 1000 residents, reflects the size of the hospital market. It was created by the Dartmouth Atlas Project using American Hospital Association (AHA) and Centers for Medicare and Medicaid Services (CMS) data.

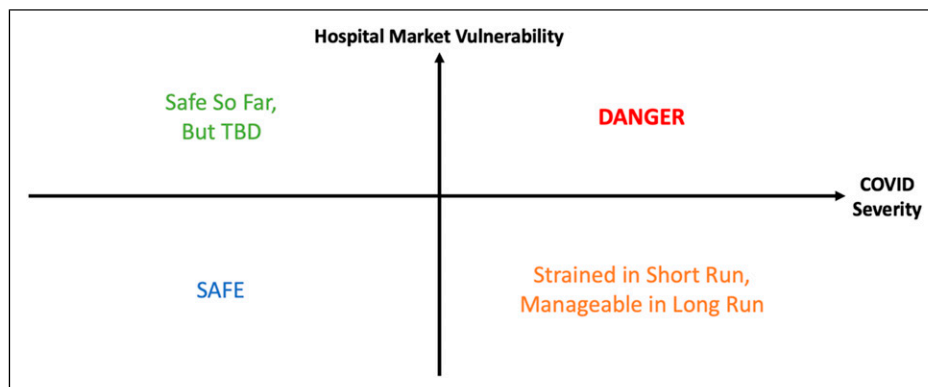


Figure 1. Analytical framework.

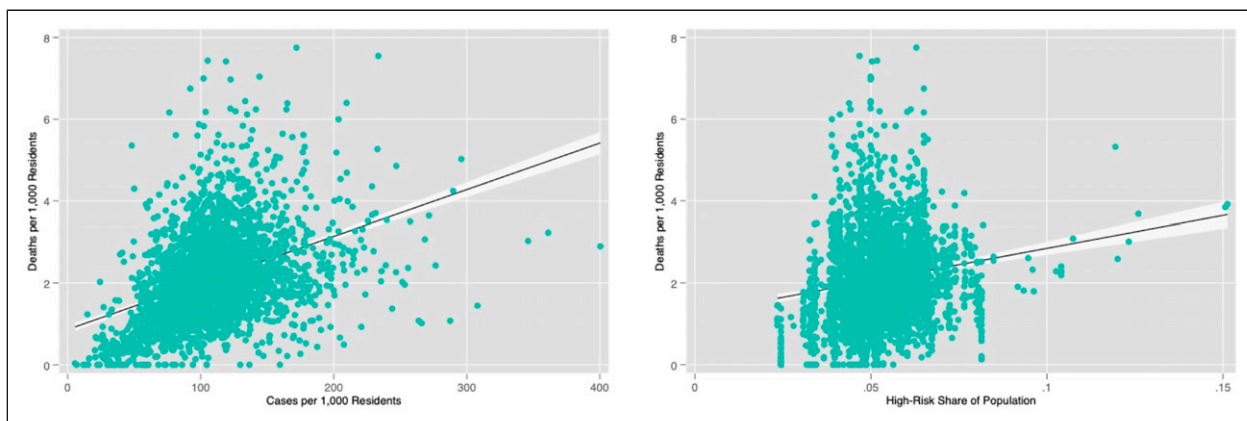


Figure 2. Measures of COVID severity.

Table 1. Pairwise Correlations Between COVID Severity Variables.

	Cases per 1000 Residents	Deaths per 1000 Residents	High-Risk Share of Population	Non-White Share of Population
Cases per 1000 residents	1.000			
Deaths per 1000 residents	.3931***	1.000		
High-risk share of population	-.0718***	.1644***	1.000	
Non-White share of population	.0602***	.1715***	-.0025	1.000

Notes: * $P < .10$, ** $P < .05$, *** $P < .01$.

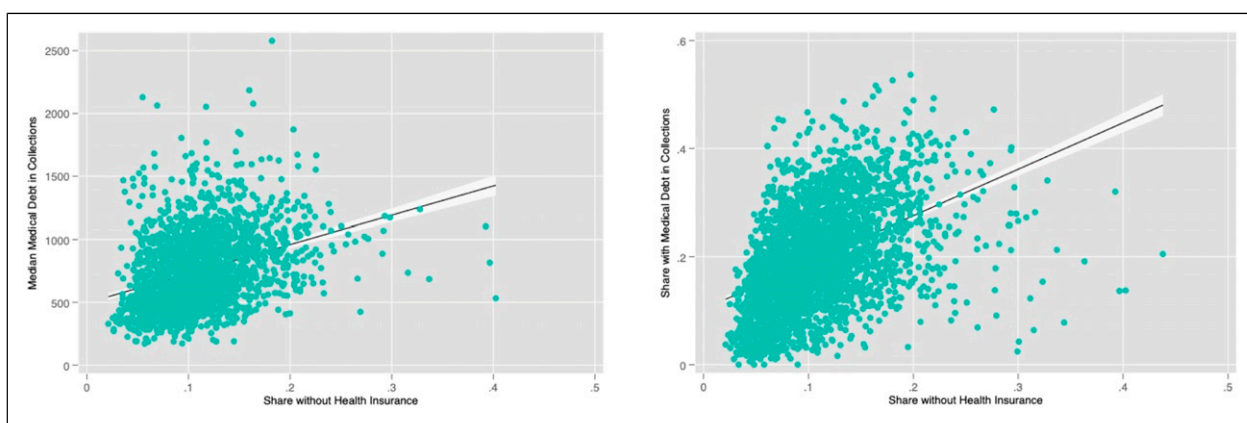


Figure 3. Different measures of hospital market vulnerability.

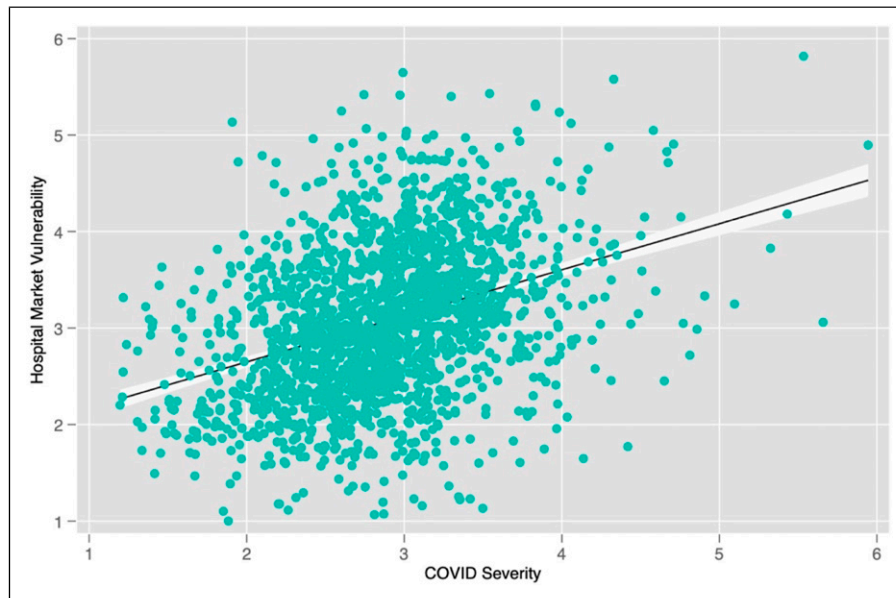
All counties are represented in this dataset, and each county has a positive (nonzero) number of hospital beds. Two of the variables, percent of intensive care unit (ICU) beds occupied and percent of inpatient beds occupied, reflect the stress on hospital capacity. They were released by the U.S. Department of Health and Human Services (HHS) on September 16, 2021. We download all these healthcare variables at the county level, rather than the hospital service area (HSA) or hospital referral region (HRR) level, in order

to merge them with the other variables, which are all available at the county level. The final 3 come from the Urban Institute: median household medical debt, share of the population with medical debt, and uninsured share of the population. They reflect the overall risk that care in a county will be uncompensated. These variables are strongly correlated (see Figure 3). For example, a 10% increase in the uninsured rate is associated with \$23,166 higher median medical debt ($P = .000$) and an 8.6% increase in the share of

Table 2. Pairwise Correlations Between Hospital Market Vulnerability Variables.

	Acute Care Beds per 1000 Residents	Median Household Medical Debt	Population with Medical Debt (%)	Uninsured Share of Population	Inpatient Beds Occupied (%)	ICU Beds Occupied (%)
Acute care beds per 1000 residents	1.000					
Median household medical debt	-.0322	1.000				
Population with medical debt (%)	.0230	.3237***	1.000			
Uninsured share of population	.0154	.3521***	.4540***	1.000		
Inpatient beds occupied (%)	.0034	-.1744***	.2309***	.0650***	1.000	
ICU beds occupied (%)	-.0001	-.0060	.4203***	.2365***	.6030***	1.000

Notes: * $P < .10$, ** $P < .05$, *** $P < .01$.

**Figure 4.** Hospital market vulnerability vs COVID severity, by county.

the population with medical debt ($P = .000$). The full set of pairwise correlations is reported in Table 2. Of the 15 pairs of variables, 9 are statistically significant at the .1% level. These correlations support their combination into a single factor for hospital market vulnerability.

We use these 2 sets of variables to create indices using factor analysis to identify a common component. We first identify factors using principal-components factoring. Next, we rotate the factor loads to produce orthogonal factors. Then, we predict the primary factor for each county. This common component is a linear combination of the variables that represents their correlated joint variation. We index these 2 factors by setting the minimum level to 1 in calculating the COVID-19 Severity Index and the Hospital Market Vulnerability Index. Finally, we multiply these indexes by each

other to create a “Danger Index,” representing the overall likelihood of financial distress for hospitals in a market.

Results

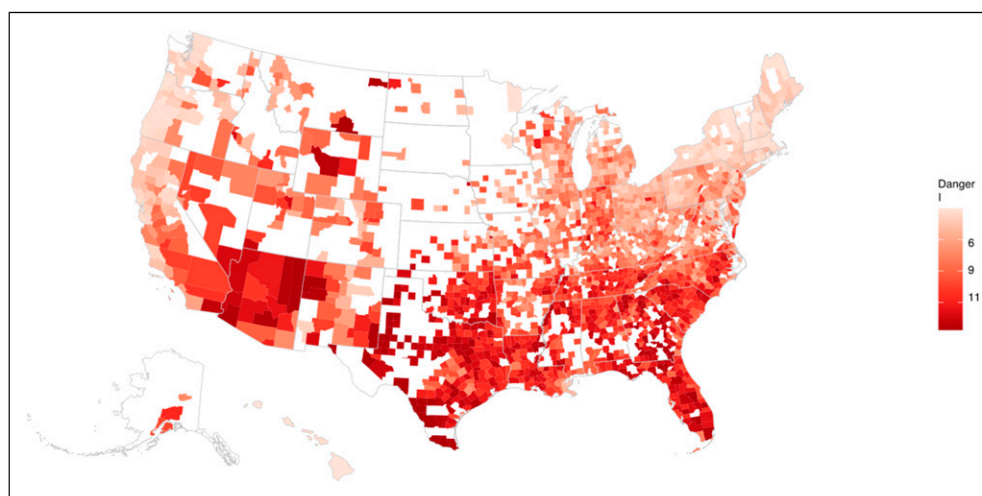
The COVID Severity Index and Hospital Market Vulnerability Index are significantly positively correlated, but the relationship only explains 13.3% of the variation across counties (see Figure 4). Thus, neither index alone—and none of the individual variables on its own—is sufficient to understand the financial distress that hospitals are likely to experience in each county. Therefore, we created our analytical framework to reflect the interaction of these factors.

If we lay this analytic framework over Figure 4, we can envision the counties falling into the 4 quadrants, divided by

Table 3. Models Predicting Hospital Closures.

	Linear Probability Model	Probit Model	Logit Model
Danger index	.0007** (.0003)	.0910** (.0391)	.2268** (.0892)
Constant	-.0043* (.0025)	-3.9522*** (.5349)	-8.9326*** (1.3541)
Observations	1940	1940	1940
R ²	.0032	.1053	.0921

Notes: * $P < .10$, ** $P < .05$, *** $P < .01$.

**Figure 5.** “Danger index” of hospital financial distress.

the midpoint of the x -axis (where the COVID-19 Severity Index is 3.5) and the midpoint of the y -axis (where the Hospital Market Vulnerability Index is also 3.5). Using this categorization, we find that 65% of the counties fall into the “safe” quadrant, 7% fall into the “strained in the short run, manageable in the long run” quadrant, 23% fall into the “safe so far, but TBD” quadrant, and the remaining 5% fall into the “danger” quadrant. Thus, our Index, which represents the product of the 2 indices, identifies a very select group of counties that are facing the most potential distress.

To validate that this Index does identify financial distress, we can use it to predict hospital closures. While there is no comprehensive, publicly available dataset on hospital closures, the Cecil G. Sheps Center for Health Services Research at the University of North Carolina maintains and publishes the most widely used list in the field. As the Danger Index is related to the accumulated burden of COVID-19, it is only appropriate to focus on hospital closures that can be reasonably attributed to the pandemic. Using this dataset, we regress the closures from August 2020 onward, after the pandemic has had sufficient time to affect hospital finances, on our Danger Index. This outcome variable includes closures up to and including July 2021. [Table 3](#) indicates that the Danger Index is a statistically significant predictor of these closures using a linear probability model, a logit model, and a probit model to ensure

robustness across specifications. The linear probability model indicates that a 1 point increase in the Danger Index is associated with a .07 percentage point increase in the probability that a county will experience a hospital closure. It is important to remember that a very small percentage of counties experience a hospital closure during this time period; the unconditional probability is .4%. Thus, the Danger Index represents a 17.5% increase in this probability—an economically meaningful increase, especially given such a short time period and small sample size for the outcome variable. Future research can continue to validate it using closures over the years to come, as the Danger Index is intended to be forward-looking.

The Danger Index shows clear geographic patterns. [Figure 5](#) visualizes these patterns with a heat map, where darker shades indicate greater likelihood of financial distress in a hospital market. White regions indicate areas where the Danger Index is not measured because 1 of the variables is unavailable. The Danger Index is highest in the southern states and in counties scattered throughout the northern plains states. The county that scores the highest on the Danger Index is Big Horn County, Montana, whose population is majority Native American, as it overlaps with the Crow Reservation. The next-highest scoring counties are Maverick County and Dimmit County in Texas. In both counties, the median income is less than \$10,000, and over

30% of the population falls below the poverty line, making them 2 of the poorest counties in the United States.

These examples suggest that the Danger Index is likely to be higher in lower-income, rural areas, where hospitals were already financially strained before the pandemic. This is consistent with prior research that examined regional COVID-19 risk alone.⁸ We test this hypothesis with a multivariate regression of the Danger Index on county-level census variables. We select these variables based on publicly available economic, demographic, and health policy-related data that have been associated with health care access (or lack thereof) historically. The economic and demographic data come from the U.S. Census Bureau, and the health policy-related data come from the U.S. Health Resources and Services Administration. This analysis shows that the Danger Index is significantly correlated with higher poverty rates, lower population density, lower household income, higher foreign-born share of the population, and higher non-White share of the population (see Figure 6). All variables are statistically significant at the $P < .01$ level. The population density variable, in particular, confirms previous research identifying rural hospitals at acute risk of financial distress. It shows that a 10% decrease in population density is associated with a 2.8-point higher Danger Index, roughly 10% of the range that the Index spans ($P = .000$). The elderly share of the population is not statistically significant. The shares of Medicaid eligible and dual eligible persons, as well as the designation as a “Health Professional Shortage Area” (HPSA), have a small effect after controlling for the other variables. Together, these variables explain 51.3% of the variation in our measure of hospital financial distress across counties.

The Danger Index can be particularly useful to policymakers in targeting aid toward the areas in greatest need. As a demonstration of this application, we compare the Index to the distribution of aid dispensed by HHS through the CARES Act Provider Relief Fund. (The HHS data are available at the city level. We map each city to its respective county using the United States Cities Database available at <https://simplemaps.com/data/us-cities> and aggregate up at the county level.) We use aid per capita as an indication of the overall amount of funding reaching a market. Of course, other types of aid are also available, but this fund was specifically targeted to financial distress that was directly related to COVID-19. As Figure 7 indicates, there is a small but positive relationship: more distressed counties received more provider relief, on average, but there are many outliers that receive much more or less than comparable counties. Regression analysis reveals that each point increase in the Danger Index is associated with a statistically significant increase of \$5.81 per capita in provider relief ($P = .002$). This finding likely reflects the additional money dedicated to rural hospitals and hospitals with a high number of COVID-19 patients. However, the weakness of the relationship in explaining the cross-sectional variation ($R^2 = .5\%$) is concerning, as it suggests that much of the aid was not allocated based on actual financial need.

Finally, we test the robustness of the Danger Index by considering an alternative approach to measuring COVID severity. In our preferred method above, we use the *cumulative* cases and deaths, which reflect the full, sustained impact of the pandemic on hospital finances over time. However, the pandemic has also raised concerns about the *peak* cases and deaths—that is, the highest level that they have reached in each county at any point during the pandemic. Although this

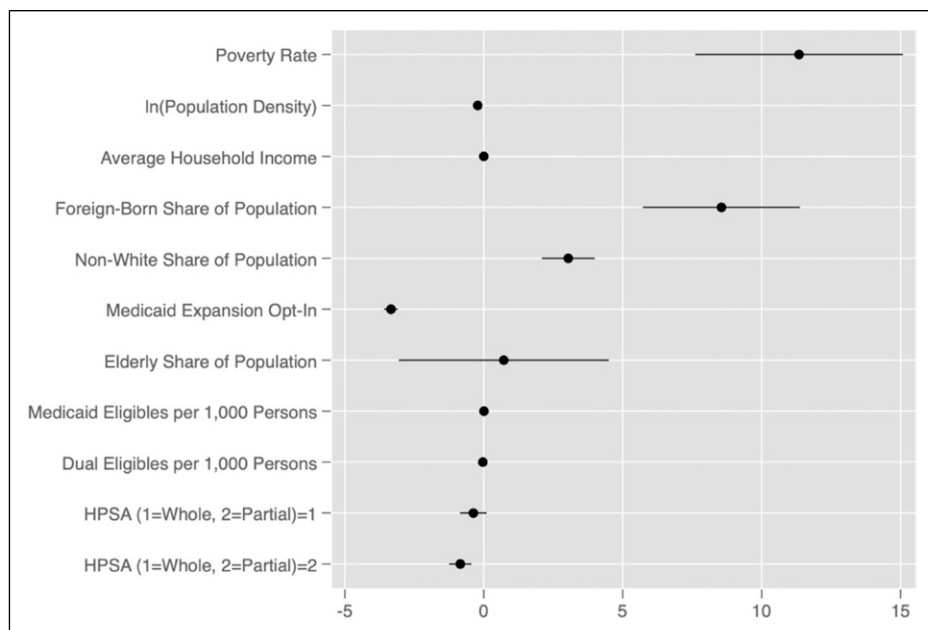


Figure 6. County-level correlates of the danger index.

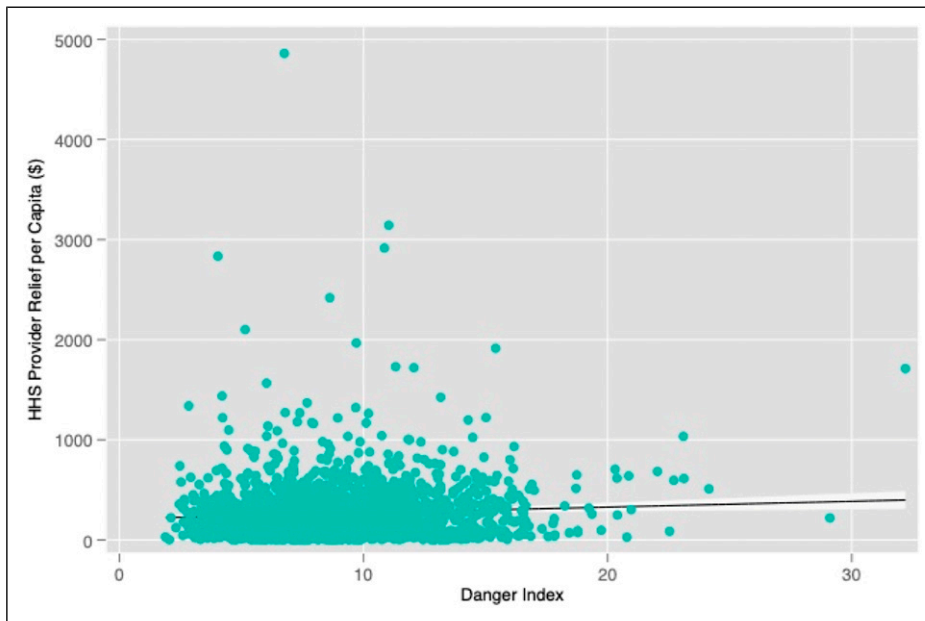


Figure 7. Health and human services provider relief per capita vs “danger index” of financial distress.

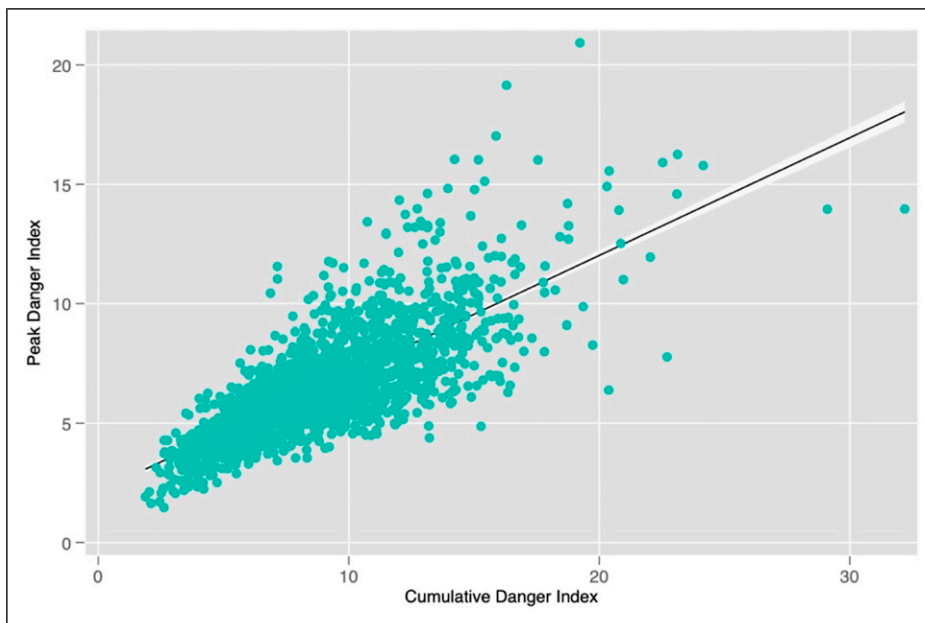


Figure 8. Two measures of “danger index”: peak vs cumulative cases and deaths.

measure does not reflect a sustained financial impact, it does measure the most strain that has been placed on the hospital’s capacity to treat patients. We measure this peak by taking a 7-day moving average of cases and deaths and then selecting the highest single observation of this moving average in each county. We replicate the construction of the COVID Severity Index with these 2 measures instead of the previous cumulative measures, and then we use this new Index to calculate a new Danger Index. As [Figure 8](#) shows, it is very tightly correlated

with the original Danger Index. In regression analysis, we confirm that this relationship is highly statistically significant ($P = .0000$), indicating that our methodology is robust to this change in COVID severity measure.

Conclusion

As the pandemic continues to strain hospital finances, some to the point of institutional closure, our estimates reveal a

level of risk that is easily neglected. The Danger Index reflects key factors affecting the level of financial stress in hospital markets that are likely to linger after the pandemic is over.

The highest level of risk appears to be concentrated in rural counties, as previous research has shown, but not in all rural counties. It is correlated with higher poverty rates, higher shares of foreign-born and non-White populations, and state governments that opted out of the Medicaid expansion. The map in [Figure 5](#) shows these counties to be located predominantly in the plains states, stretching from western Texas and Oklahoma up to the Dakotas and Minnesota, where COVID-19 infection rates were spiking most severely in late 2020.⁹

These findings point not only to counties struggling with a pandemic that has strained their hospital capacity but also to counties at risk of losing health care access altogether. Our focus on hospital markets rather than individual hospitals highlights these areas, which tended to have few available beds before the pandemic began. Loss of hospital capacity would have a particularly severe effect on their residents. By identifying these counties, our Index can help government programs target resources to areas where they are most needed as the country rebuilds its health care system and prepares for crises to come. Finally, it sets the stage for future research that can build upon these variables and this methodology to explore the heterogeneity of financial distress within counties, using hospital-level data to inform more localized targeting of policies.

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ORCID iD

Anthony W. Orlando  <https://orcid.org/0000-0003-3397-5368>

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