Estimating the Burden of COVID-19 Associated Hospitalizations in Connecticut

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Abstract

The number of COVID-19 related hospitalizations that occur in a particular area is dependent on a variety of sociodemographic and clinical factors, but the percentage of hospitalizations that are identified in that region varies based on the type and quality of surveillance system that is utilized. In Connecticut, an active surveillance system called the COVID-19–Associated Hospitalization Surveillance Network (COVID-NET) conducts COVID-19 associated hospitalization surveillance in two of Connecticut's eight counties. The other counties in Connecticut rely on a passive surveillance system which could be subject to underreporting. To evaluate possible underreporting, positive SARS-CoV-2 test rates obtained from the Connecticut Department of Public Health (CT DPH) and variables from the CDC's Social Vulnerability Index (SVI) were used as covariates in a negative binomial regression model. The model was fit to random samples of COVID-NET hospitalization data through an iterative process and ten optimal models were selected using stepwise Akaike's Information Criterion (AIC). The average of the regression coefficients for each covariate included in the ten optimal models was calculated and multiplied by a model matrix containing the original SVI and SARS-CoV-2 testing covariates for each census tract in Connecticut to produce census tract-level estimates of COVID-19 related hospitalizations in Connecticut. Based on the model estimates, 5,600 excess hospitalizations occurred throughout 2020 compared to the number passively reported to CT DPH. Of note, New London County had the largest discrepancy between observed and estimated hospitalization rates (255 hospitalizations per 100,000), and New Haven and Middlesex counties (the counties which comprise the COVID-NET catchment area) had the lowest discrepancy (45 hospitalizations per 100,000 and 56 hospitalizations per 100,000, respectively). Widespread underreporting of COVID-19 related hospitalizations in Connecticut has broad implications. These surveillance gaps must be addressed to achieve more equitable pandemic planning and response.

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Table of Contents

Tables & Figures

Introduction

COVID-19 is the largest public health crisis in over a century. To date, over six million people have lost their lives to COVID-19, and nearly one million of those deaths occurred in the United States [1,2]. Although COVID-19 has caused global suffering, the worst clinical outcomes of COVID-19 have not fallen equally across populations. Clinical factors, such as heart disease and chronic lung disease, have put individuals at risk for serious illness [3]. In the United States, sociodemographic characteristics like race, income, employment status, and housing type have been strong determinants of severe COVID-19 outcomes, and have brought to light structural and systemic disparities in the American healthcare system and in society more broadly [4].

Due to the severity of COVID-19 and its disproportionate effect on certain populations, it is important to have effective surveillance systems that can track cases, hospitalizations, and deaths attributed to COVID-19. Doing so gives insight into the burden of disease in a particular area and can guide priority setting and resource allocation among public health practitioners and policymakers [5]. Within the context of public health, there are two major types of surveillance: active and passive. Passive surveillance is defined as a system by which hospitals, clinics, and other public health sources send reports of disease to departments of health, health ministries, or other public health institutions [6]. In Connecticut, a passive surveillance system is used to track COVID-19 related hospitalizations. Although passive surveillance is beneficial, there are instances in which it could underestimate the number of cases of disease in a population [6]. For example, a lack of active follow-up with reporting agencies about potential cases could lead to underestimations. In the case of the Connecticut Department of Health (CT DPH), COVID-19 related hospitalizations are reported in a database called the Connecticut Electronic Disease Surveillance System (CTEDSS), but there is not a system in place to audit healthcare facilities for information related to hospitalizations that could have been unreported.

Unlike passive surveillance systems, active surveillance systems have staff who are employed to contact health facilities to collect data on reportable health conditions [6]. An example of this is the COVID-19–Associated Hospitalization Surveillance Network (COVID-NET), which is a CDC-funded, multisite, active surveillance system of COVID-19 related hospitalizations that has a surveillance site in Connecticut.

The motivating factor underlying this research is the potential disparity in reported COVID-19 related hospitalizations between CT COVID-NET's active surveillance system and CT DPH's passive surveillance system. It was hypothesized that CT COVID-NET, an active surveillance system, would have reported more COVID-19 related hospitalizations in 2020 than what was reported passively to CT DPH in CTEDSS. However, the catchment area for CT COVID-NET includes only two of Connecticut's eight counties. Therefore, a traditional epidemiological approach was not appropriate to conduct a statewide comparison of hospitalizations reported by COVID-NET to hospitalizations recorded in CTEDSS. Instead, a statistical modeling approach was used to fit a negative binomial regression model to COVID-NET data and to estimate the number of COVID-19 related hospitalizations occurring in Connecticut census tracts throughout 2020. Estimates produced by the model were then compared to hospitalizations passively reported to CT DPH. Because clinical and sociodemographic risk factors for COVID-19 are not spread uniformly throughout populations and geographics regions, incidence of positive SARS-CoV-2 tests and variables from the CDC's Social Vulnerability Index (SVI) were used as covariates in the model to account for census tract level differences in COVID-19 risk factors (**Figure A1**).

Methods

Data

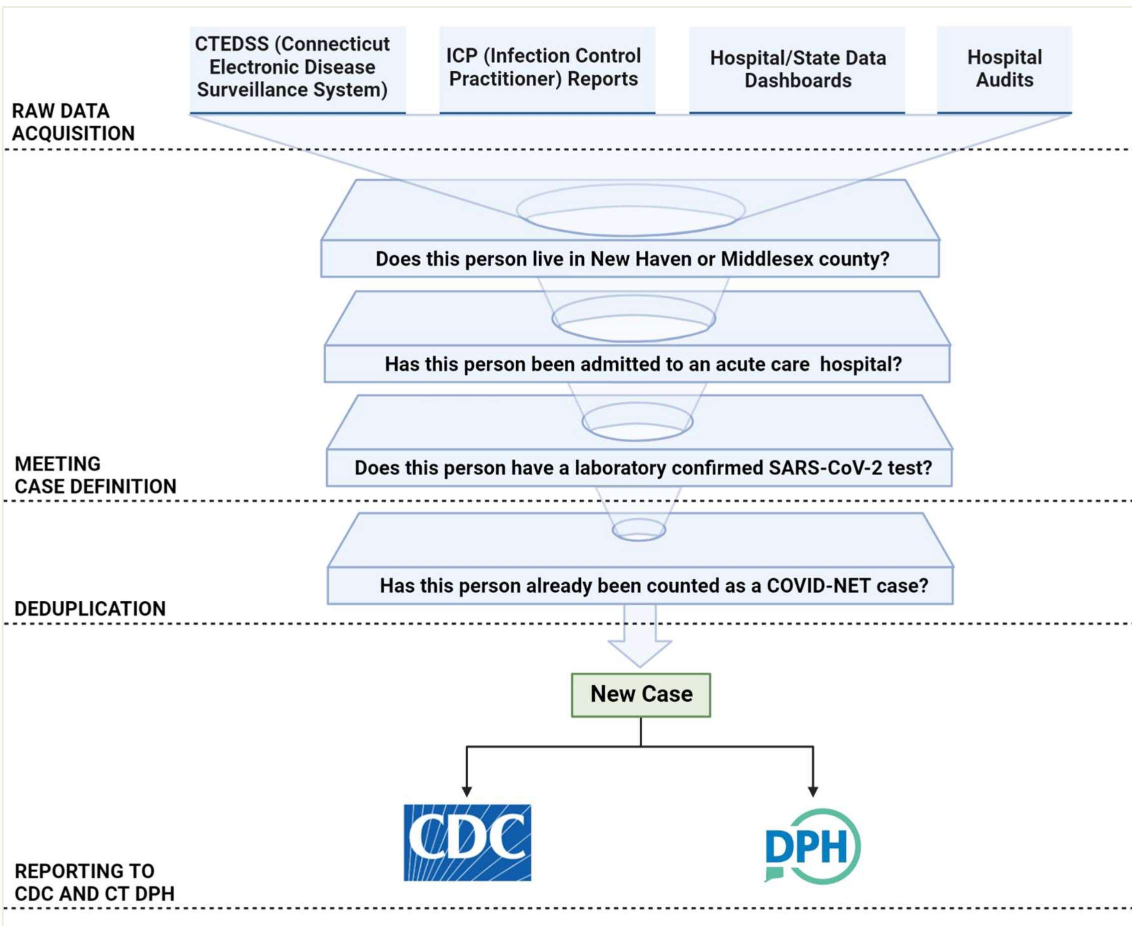
COVID-NET

COVID-NET was created in March 2020 in response to the COVID-19 pandemic. It was built from the existing infrastructure of the Influenza Hospitalization Surveillance Network (FluSurv-NET) and the Respiratory Syncytial Virus Hospitalization Surveillance Network (RSV-NET) with the purpose of conducting surveillance of laboratory-confirmed COVID-19 related hospitalizations in the United States [7]. In its entirety, the COVID-NET catchment area includes 99 counties in 14 states, representing 10% of the United States population [7,8]. Patients who live in a COVID-NET catchment area and are hospitalized within 14 days of a laboratory-confirmed SARS-CoV-2 test meet the COVID-NET case definition [7]. Patients who receive a laboratory confirmed SARS-CoV-2 test during their hospitalization are also counted as COVID-19 cases. The catchment area of the CT COVID-NET site encompasses New Haven and Middlesex counties, including slightly over 1 million residents. The generalized COVID-NET case definition is used by CT COVID-NET, but hospitalized COVID-19 patients must be residents of New Haven or Middlesex counties to meet the CT COVID-NET case definition.

Although CT COVID-NET is an active surveillance site, it conducts both active and passive case-finding. COVID-19 related hospitalizations passively reported by infection control practitioners (ICPS) through CTEDSS are documented and reported by CT COVID-NET (**Figure 1**). Active case-finding is conducted using hospital audits and hospital and state data dashboards (**Figure 1**). All acute care facilities in New Haven and Middlesex counties except the Connecticut VA have been routinely audited for potential COVID-NET cases since March 2020. The Connecticut VA differs from private hospitals in their data access and reportable disease policies and does not participate in COVID-NET's auditing system for this reason. After a COVID-NET case is identified, the CT COVID-NET team conducts full or partial chart reviews using patient medical records.

For this study, the CT COVID-NET team provided a dataset of all 2020 CT COVID-NET cases as reported in its REDCap database. All cases with existing addresses were geocoded to 2010 census tracts.

Figure 1. CT COVID-NET case-finding protocol



CT DPH

In July 2020, the public health statutes that regulate reportable diseases in Connecticut were amended to include COVID-19 associated hospitalizations [9]. Since this amendment was created, all institutions and organizations that collect data on patients hospitalized with COVID-

19, including COVID-NET, have been required to report hospitalizations in CTEDSS [9]. Because of this, COVID-NET data are represented in the CTEDSS dataset used in this study.

CT DPH provided statewide counts of COVID-19 related hospitalizations and positive SARS-CoV-2 tests that occurred in 2020 and were reported in CTEDSS. To meet inclusion criteria for this dataset, a patient had to be a Connecticut resident and hospitalized at an acute care hospital within 14 days of a positive SARS-CoV-2 test. Because many hospitalizations in CTEDSS do not include a discharge date, individuals who tested positive for SARS-CoV-2 one to four days after their hospital admission date were also included in the dataset.

Each hospitalization and positive test was matched to its relevant census tract. If a person had multiple positive tests during 2020, a ten-week lag between positive tests was necessary for the subsequent test to be considered a true infection. If someone was hospitalized multiple times with a laboratory confirmed COVID-19 infection, a two-week lag between admissions was necessary for the subsequent admission to be counted as a true COVID-19 associated hospitalization.

SVI

The CDC's Social Vulnerability Index (SVI) was created with the intention of helping public health officials and emergency response planners identify socially vulnerable communities that would be at highest risk before, during, and after a hazardous event [10]. It includes 16 different variables that are separated into four major categories: socioeconomic status, household composition & disability, minority status & language, and housing type & transportation [10]. The dataset containing 2018 SVI variables for Connecticut census tracts was obtained from the CDC/ATSDR SVI Data and Documentation Download website (https://www.atsdr.cdc.gov/placeandhealth/svi/data_ documentation_download.html).

Denominators

Denominators used in the calculation of hospitalization rates by race for Connecticut census tracts were extracted from Table P1 of the 2010 Decennial Census (https://data.census.gov/cedsci/table?g=0400000US09%240500000&tid=DECENNIALPL2020.P1). Values in Table P1 were also used to calculate the overall hospitalization rate and county-level hospitalization rate for CT COVID-NET and CT DPH. Values were extracted from Table P9 of the 2010 Decennial Census to calculate hospitalization rates by Hispanic ethnicity (https://data.census.gov/cedsci/table?q=p9&g=0400000US09%240500000&tid=DECENNIALSF12010.P9). Values from Table PCT12 from the 2010 Decennial Census were used to calculate hospitalization rates by sex and age (https://data.census.gov/cedsci/table?q=age&g=0400000US09%240500000&d=DEC%20Summary%20File%201&tid=DECENNIALSF12010.PCT12).

Model Training & Selection

Census tract-level SVI variables and positive SARS-CoV-2 testing rates were used as covariates in this study. All variables were standardized before being used in the analysis because SVI and testing variables were measured on different scales. A Poisson regression model was originally fit to CT COVID-NET hospitalization counts aggregated by census tract. However, there was evidence of overdispersion in the data after model fitting, so a negative binomial model was selected instead.

A random sample of 10% of New Haven and Middlesex census tracts were subset to create a holdout sample for model training and selection, and a negative binomial regression model was fit to the remaining 90% of New Haven and Middlesex census tracts. Stepwise model selection by Akaike's Information Criterion (AIC) was used to select the covariates which best fit the training data. The optimal model as determined by stepwise AIC was then used to estimate the number of hospitalizations for each census tract of the holdout sample. This process of model fitting and selection was repeated ten times, and for each replication of this process, regression coefficients and predicted values were extracted for further analysis.

Estimating COVID-19 Related Hospitalizations for Connecticut

The variables selected in the optimal model for each iteration depended on the training data randomly selected for that iteration. For each instance of a variable being excluded from an optimal model, the corresponding missing values in the regression coefficient matrix were replaced with zeroes. The mean estimate of the regression coefficients generated from the updated matrix was then calculated. SVI variables and the positive SARS-CoV-2 testing rates for all census tracts in Connecticut were then used as covariates in a model matrix. The model matrix was then multiplied by the mean estimates of the regression coefficients to generate estimations on a log-scale. The result was exponentiated to produce estimated census tract-level hospitalization counts.

Comparison of Statewide Estimates to Observed Values

The sum of the estimated number of COVID-19 related hospitalizations was subtracted from the sum of COVID-19 related hospitalizations reported by CT DPH through CTEDSS to obtain an initial estimate of unreported COVID-19 related hospitalizations across the state. Using population denominators from the 2010 Decennial Census, estimated and observed hospitalization rates per 100,000 were calculated for each census tract. A linear regression model was fit to the observed hospitalization rates, and the estimated hospitalization rate was used as the predictor. The intercept of the regression line was used to determine if there was underreporting of COVID-19 related hospitalizations in CTEDSS. Subtracting the exponentiated slope of the regression line from one gave the proportion of COVID-19 associated hospitalizations that were captured by CTEDSS. Estimated and observed hospitalization counts were aggregated by county and converted to rates for further comparison.

Results

From March 14, 2020 through December 31, 2020, there were 14,472 COVID-19 related hospitalizations reported to the Connecticut Department of Public Health through CTEDSS (**Table 1**). Based on estimates produced by the model, there were approximately 19,000 COVID-19 related hospitalizations in Connecticut during 2020, meaning that the model estimated about 5,500 (40%) more hospitalizations than what was reported to CT DPH in CTEDSS (**Table 2**).

When hospitalizations were aggregated by county and converted to rates, New Haven and Hartford counties had the highest observed hospitalization rates: 535 hospitalizations per 100,000 and 395 hospitalizations per 100,000, respectively (**Table 2**). However, modeled results estimated Fairfield and New Haven counties to have the highest hospitalization rates at 640 hospitalizations per 100,000 and about 580 hospitalizations per 100,000 (**Table 2**). When estimated county-level hospitalization rates were subtracted from observed hospitalization rates, New London County showed the largest discrepancy between modeled and observed values at 255 hospitalizations per 100,000 (**Table 2**). New Haven and Middlesex, the counties that comprise CT COVID-NET's catchment area, had the lowest difference between modeled and observed hospitalization rates. The differences between modeled and observed values for these counties were 45 hospitalizations per 100,000 and 56 hospitalizations per 100,000, respectively (**Table 2**).

After the model fitting and selection process, fifteen of the sixteen different covariates appeared in at least one of the ten optimal models. Seven covariates were included in all ten optimal models: positive SARS-CoV-2 test rate, percentage of persons 65 and older, percentage of the civilian non-institutionalized population with a disability, percentage of individuals meeting minority status (which includes all persons except white, non-Hispanic

Table 1. Characteristics of geocoded COVID-19 patients who were hospitalized during 2020 as recorded by CT COVID-NET and CT DPH

	Counts (%)		Rates (per 100,000)	
	COVID-NET[a]	CTEDSS[b]	COVID-NET	CTEDSS
n	6156	14472	598.74	401.34
County				
Middlesex	614 (10.7)	537 (4.0)	373.83	326.95
New Haven	5148 (89.3)	4599 (34.0)	595.26	531.78
Fairfield		3516 (26.0)		367.24
Hartford		3491 (25.8)		388.11
Litchfield		472 (3.5)		254.88
New London		467 (3.4)		173.89
Tolland		228 (1.7)		152.22
Windham		234 (1.7)		201.00
Age				
≤ 9	21 (0.3)	55 (0.4)	17.75	12.95
10-19	42 (0.7)	109 (0.8)	30.04	22.20
20-29	190 (3.1)	479 (3.3)	142.76	108.36
30-39	355 (5.8)	817 (5.6)	287.48	190.61
40-49	514 (8.4)	1194 (8.3)	332.22	215.79
50-59	930 (15.1)	2225 (15.4)	622.54	424.23
60-69	1287 (20.9)	2933 (20.3)	1244.75	831.88
70-79	1330 (21.6)	3031 (20.9)	2351.78	1555.04
≥ 80	1486 (24.1)	3629 (25.1)	3007.12	2235.12
Race				
White	3433 (55.8)	7803 (53.9)	433.15	281.45
Black	1298 (21.1)	2480 (17.1)	1103.96	684.52
Asian/Pacific-Islander	70 (1.1)	255 (1.8)	200.56	186.14
Hispanic/Latino	1143 (18.6)	3122 (21.6)	830.81	651.66
American Indian or Alaska Native	7 (0.1)	12 (0.1)	254.55	106.61
Multiracial	25 (0.4)	359 (2.5)	26.68	387.37
Not specified	176 (2.9)	441 (3.0)		
Sex				
Female	3037 (49.3)	6957 (48.1)	570.70	379.23
Male	3119 (50.7)	7494 (51.8)	628.83	430.79
Unknown	0 (0.0)	21 (0.1)		

[a] Individuals who are residents of New Haven or Middlesex counties and who are hospitalized at an acute care hospital within 14 days of a laboratory confirmed SARS-CoV-2 test are considered COVID-NET cases. Those who receive a laboratory confirmed SARS-CoV-2 test during their hospitalization are also included in the COVID-NET dataset. [b] Individuals who are Connecticut residents and hospitalized at an acute care hospital within 14 days of a positive SARS-CoV-2 test were included in the CT DPH/CTEDSS dataset. Individuals who tested positive for SARS-CoV-2 one to four days after their hospital admission date were also included.

individuals), percentage housing in structures with 10 or more units, percentage of persons (age 5+) who speak English "less than well," and the percentage of uninsured individuals in the total civilian noninstitutionalized population. On average, the percentage of individuals meeting minority status (β = 0.331) had the largest positive association with hospitalizations, followed by the percentage of individuals aged 65 or older (β = 0.213) (**Table A1**). Percentage of households with no vehicle available and the percentage of persons (age 5+) who speak

Table 2. Observed and estimated COVID-19 related hospitalizations from March 14, 2020 to December 31, 2020

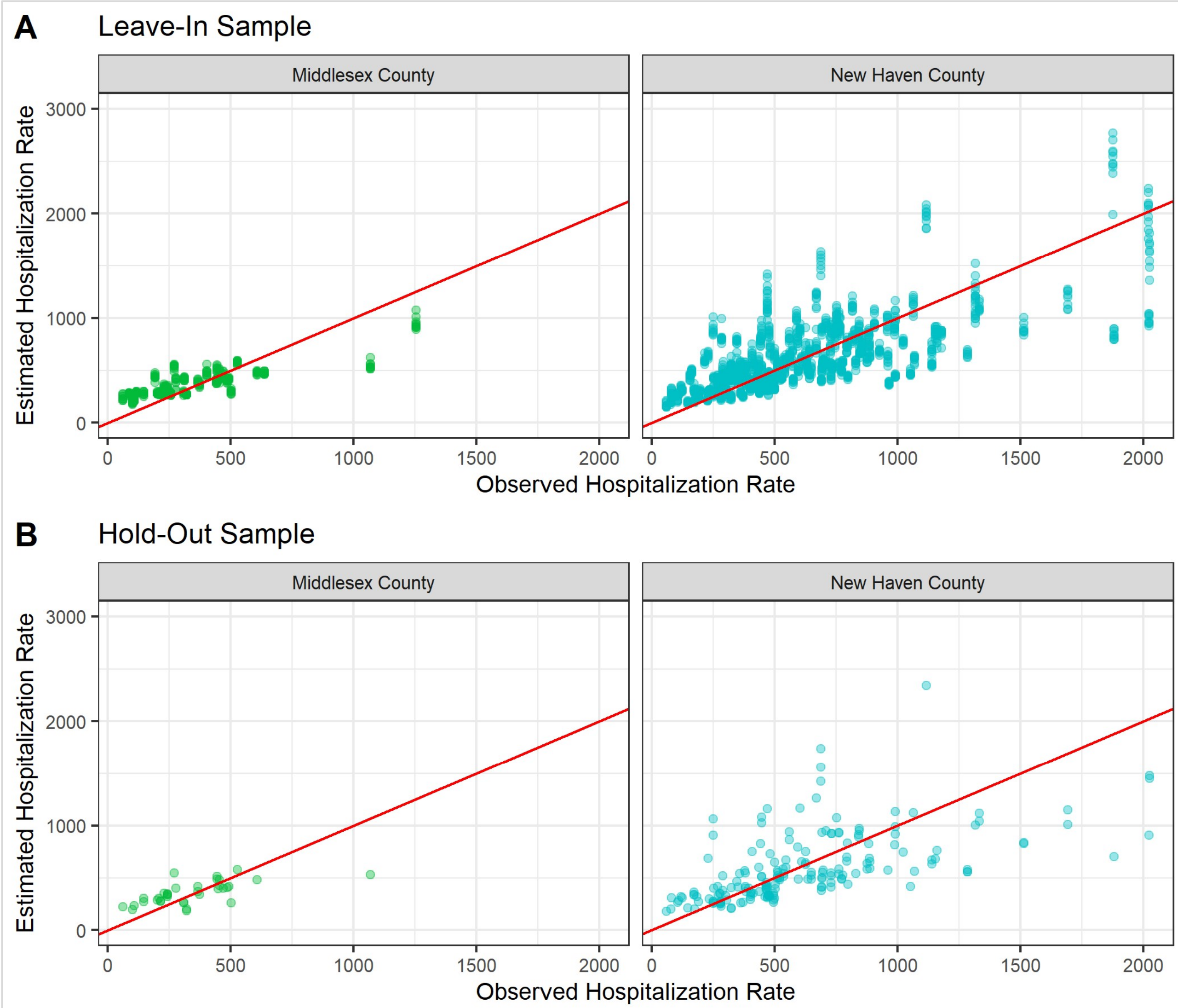
	Counts		**Rates (per 100,000)**		
County	**Observed**	**Estimated**	**Observed**	**Estimated**	**Difference**
Fairfield	3,516	5,800	386	640	254
Hartford	3,491	5,100	395	570	175
Litchfield	472	650	264	370	106
Middlesex	537	630	324	380	56
New Haven	4,599	5,000	535	580	45
New London	466	1,100	175	430	255
Tolland	215	430	157	310	153
Windham	234	440	198	370	172
Total	13,530	19,000	384	540	160

Observed values were reported by CT DPH through CTEDSS. Estimated values were produced by the model. Total values do not equal the sum of estimated values by county due to rounding.

English “less than well” had the strongest negative association with hospitalizations ($\beta = -0.173$ and $\beta = -0.132$, respectively) (**Table A1**).

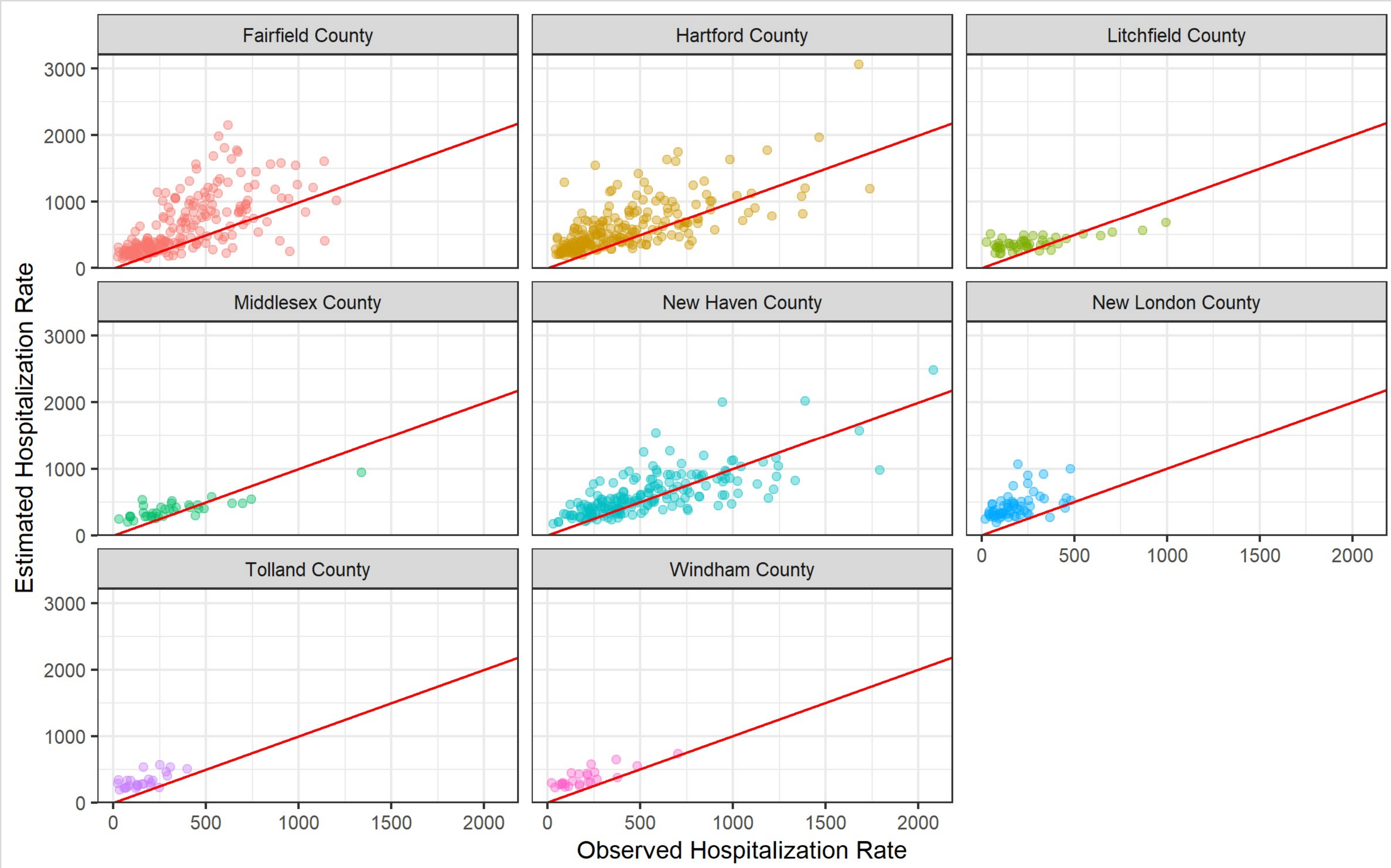
When a linear model was used to determine how well estimated rates predicted observed rates, the slope of the regression line was 1.05, and its intercept was -0.83. Subtracting the exponentiated slope from one to determine the degree of underreporting gave a value of 0.56, or 56%.

Figure 2. Observed vs. estimated hospitalization rates of leave-in (**A**) and hold-out (**B**) samples to evaluate model fit to training data



Rates are per 100,000 population.

Figure 3. Observed vs model-estimated COVID-19 associated hospitalizations that occurred during 2020 by Connecticut county



Rates are per 100,000 population.

Discussion

The estimates produced by the model suggest that the number of COVID-19 related hospitalizations passively reported to the Connecticut Department of Public Health in 2020 captured approximately 56% of total COVID-19 related hospitalizations in Connecticut. This underreporting could be due to multiple causes. First, COVID-19 related hospitalizations did not become a reportable condition in Connecticut until July 2020 [9]. This could mean that infection control practitioners (ICPs) and other reporters in the state were not entering COVID-19 related hospitalizations into CTEDSS to the same degree as they would after it became a reportable condition. On the other hand, CT COVID-NET was actively auditing hospitals in its catchment area and capturing COVID-19 hospitalizations since March 2020. In addition to this, the beginning of the pandemic in the United States was marked by a major shortage of SARS-CoV-2 testing [11]. Large hospital systems in the COVID-NET catchment area, specifically the Yale New Haven Health System, could have acquired more tests and had better reporting capacity when compared to smaller hospital systems in other counties in Connecticut. Connecticut residents living in towns which border New York, Massachusetts, and Rhode Island could have also sought care at out-of-state hospitals at higher rates than residents living in New Haven and Middlesex counties–both of which do not border another state. Although all Connecticut residents with a COVID-19 related hospitalization should be reported to CT DPH regardless of where the patient is hospitalized, reporting is less reliable across state lines. Finally, technical issues surrounding the deduplication process in CTEDSS could have also contributed to a lower number of COVID-19 related hospitalizations reported to CT DPH. Throughout 2020, there was a single case report form per person hospitalized with COVID-19. If someone was hospitalized with COVID-19 more than once in 2020, the original hospitalization could have been overwritten by subsequent hospitalizations (A. Edmundson, pers. comm.).

Evidence of underreporting in CTEDSS was further supported by evaluating the linear model used to assess the relationship between estimated and observed COVID-19 related hospitalizations in Connecticut. The slope of the regression line was 1.05 and its intercept was -0.83. Both the slope and the intercept were significant. Because the intercept was negative, evidence of underreporting was further supported.

Since the discrepancy between observed and estimated values for New Haven and Middlesex census tracts was the smallest out of all Connecticut counties, the number of COVID-19 related hospitalizations reported in CTEDSS was semi-representative of the number of COVID-NET cases detected throughout 2020. A reason for this is CT COVID-NET is required to report all COVID-19 related hospitalizations to CT DPH through CTEDSS. Therefore, modeled estimates of COVID-19 related hospitalizations in the COVID-NET catchment area should be representative of the observed number of hospitalizations reported in CTEDSS.

The three covariates that were the strongest predictors of hospitalization rates were minority status, age, and positive test incidence. Throughout the course of the pandemic, age has been a major risk factor associated with hospitalization for COVID-19, meaning census tracts with older populations could have a stronger association with higher hospitalization rates [7,12]. The COVID-19 pandemic has also laid bare racist structures that have created racial/ethnic disparities in COVID-19 related hospitalizations throughout the United States, which could explain why minority status is one of the strongest predictors of hospitalization in this study [13,14]. The number of COVID-19 related hospitalizations occurring in a community is typically dependent on the prevalence of COVID-19 in that same community, which is why positive test incidence could be a predictor of COVID-19 related hospitalizations [15].

There were multiple limitations in this study. First, testing data that were provided by CT DPH was extracted from CTEDSS. This means it could be subject to underreporting for reasons similar to those described for hospitalization data reported in CTEDSS. Another limitation involves using SVI variables as covariates in the model. The CDC's SVI was originally created to identify communities most at risk for experiencing adverse events from any natural disaster—not just viral respiratory epidemics [10]. Therefore, this dataset is not a comprehensive list of all relevant predictors of COVID-19 related hospitalizations and excludes important risk factors such as the distribution of pre-existing conditions in a population. Finally, this analysis was conducted at the census tract level. Although census tracts are representative of neighborhoods, and neighborhoods are a determinant of health, conducting a census tract-level analysis does not capture individual-level effects [16,17].

In conclusion, the model created in this study detected underreporting of COVID-19 related hospitalizations in the Connecticut Department of Public Health’s disease surveillance system, CTEDSS, throughout 2020. If CTEDSS was failing to capture 40-50% of all COVID-19 hospitalizations in Connecticut throughout 2020, this has broad implications for the current state of the COVID-19 pandemic and for future pandemic preparedness. In the case of CTEDSS, the number of hospitalizations that were passively reported to CT DPH in 2020 underestimates the severity of COVID-19, which could mislead public health officials and policymakers about areas and populations that are suffering the worst outcomes of COVID-19. COVID-NET is fortunate to receive funding to carry out active surveillance activities throughout the United States, but in many areas of the country such as Connecticut, public health surveillance is underfunded. Although modeling approaches are useful in situations where surveillance systems are unreliable, they should not become a replacement for building stronger public health surveillance infrastructure.

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Appendix A. The Social Vulnerability Index

Figure A1. SVI variables arranged by category [10]

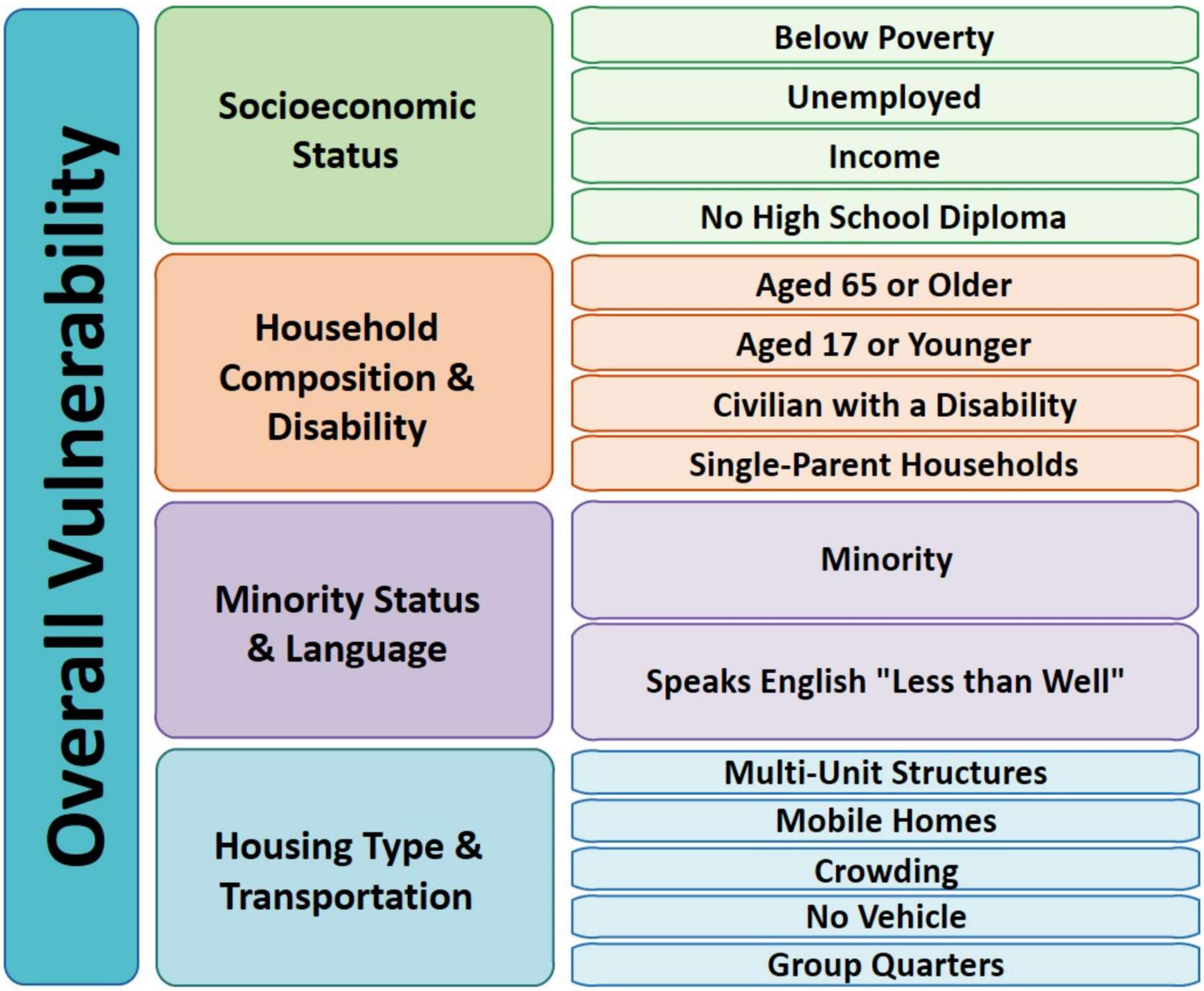

Table A1. Average magnitude and direction of coefficients from covariates included in optimal models from model training and selection

Covariates	**β**
Percentage minority (all persons except white, non-Hispanic)	0.331
Incidence of laboratory confirmed SARS-CoV-2 tests	0.277
Percentage of persons 65 and older	0.213
Percentage uninsured in the total civilian noninstitutionalized population	0.145
Percentage of housing in structures with 10 or more units	0.133
Percentage of civilian non-institutionalized population with a disability	0.074
Percentage of single parent households with children under 18	0.032
Unemployment rate	0.015
Percentage of persons below poverty	0.015
Percentage of persons aged 17 and younger	0.006
Percentage of persons with no high school diploma	-0.012
Percentage of mobile homes	-0.014
Per capita income	-0.081
Percentage of households with no vehicle available	-0.132
Percentage of persons (age 5+) who speak English “less than well”	-0.173