**The Role of SHIELD Test Centers in Reducing COVID-19 ICU Admissions in Disadvantaged Communities**

**Abstract**

**Background:** The COVID-19 pandemic, especially with the emergence of variants like Alpha, Delta, and Omicron, has created significant challenges in managing severe cases. These variants, particularly Delta, have been linked to higher ICU admissions, disproportionately affecting disadvantaged communities. SHIELD Illinois, a saliva-based COVID-19 testing program, increased testing statewide, yet its impact on COVID-19 outcomes in these communities remains uncertain. This study leverages SHIELD data to explore its effectiveness in improving outcomes in socioeconomically disadvantaged areas.

**Objective:** This study examines the relationship between the effective number of SHIELD test centers and COVID-19 ICU admission rates during the Alpha, Delta, and Omicron waves, focusing on how socioeconomic factors across zip codes influence this relationship in a large academic hospital serving Chicago’s western suburbs**.**

**Methods:** This cohort study conducted a secondary analysis using data from the Loyola University Chicago ICU’s EHR system and the SHIELD Illinois Testing Program. We analyzed data from March to June 2021 (Alpha wave), August to November 2021 (Delta wave), and December 2021 to March 2022 (Omicron wave). A linear mixed-effects regression model was employed to assess the relationship between the effective number of SHIELD test centers and COVID-19 ICU admission rates, adjusting for fixed effects such as SHIELD center density and Area Deprivation Index (ADI) score. Robustness check using a two-month lag analysis was performed to assess the timing of testing and ICU admissions across waves.

**Results:** Our results showed that disadvantaged areas consistently had higher ICU admission rates, particularly during the Delta and Omicron waves, despite increases in SHIELD test centers. Regression models indicate that while ICU rates were significantly higher in these areas, increasing the number of SHIELD centers during the Omicron wave was associated with a reduction in ICU admissions (β=-0.594, p < 0.1). A two-month lag analysis further confirmed that enhancing SHIELD center effectiveness led to lower ICU rates over time, with disadvantaged areas benefiting from targeted interventions during Omicron (β=-0.678, p < 0.1).

**CONCLUSION:** The findings emphasize the critical role of strategically deploying and optimizing the use of SHIELD test centers in disadvantaged areas to effectively reduce COVID-19 ICU admissions, especially during the Omicron wave. Targeted resource allocation is crucial for minimizing severe outcomes and ensuring equitable healthcare responses in future pandemics.

**Introduction**

The World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020, and since then, it has caused over 7 million deaths globally [1], [2], [3]. COVID-19 is a highly variable disease, with symptoms ranging from asymptomatic cases to mild, severe, or critical illness, and it can result in death in 1-2% of patients [4]. Grasselli et al., (2020) [5] highlights that COVID-19 patients experience increased rates of hospitalization and intensive care unit (ICU) admissions. Supporting this observation, Kim et al., (2021) [6] has found that among a sample of 2,491 adults hospitalized with confirmed COVID-19, nearly one-third needed admission to the ICU.

The appearance of new SARS-CoV-2 variants has posed a challenge in managing the COVID-19 pandemic [7]. The Alpha variant was the first of the major variants to emerge. It appeared in Great Britain in November 2020 and soon after became the dominant strain in the United States [8]. The Centers for Disease Control and Prevention (CDC) reported that in mid-April 2021, prior to the emergence of the more transmissible and immune-evasive Delta variant, the Alpha variant accounted for 66% of COVID-19 cases in the United States [9].

The Delta variant was first detected in India in late 2020. It rapidly spread globally and remained the dominant strain until Omicron [10] replaced it in mid-December 2021. The Delta variant is thought to have caused more than twice as many infections and deaths as the earlier variants. Following a steady decline in cases and hospitalizations in the US, the arrival of the Delta variant coincided with a swift reversal of that trend [8]. Certain studies have discovered a connection between the Alpha variant and higher rates of hospitalization, ICU admissions, and mortality [11], [12]. However, among the unvaccinated people, the Delta variant caused more severe disease which resulted in a sharp increase in hospitalizations, ICU admissions, and death [13].

The Omicron variant was first detected in Botswana and South Africa in late November 2021 and quickly started spreading to other countries. Despite being highly transmissible and immune-evasive, the Omicron does not seem to cause more severe disease than other variants [10]. Data showed that infections caused by the Delta variant are more severe, leading to lower survival rates compared to those caused by the Alpha or Omicron variants [14]. At its peak dominance in the summer of 2021, the Delta variant was estimated to be 40% to 60% more transmissible than the Alpha variant [8]. While the Omicron variant spread more rapidly than Alpha and Delta waves [15], hospital stays, ICU admissions, and death rates have been lower compared to those associated with the Delta variant [16].

The COVID-19 pandemic has disproportionately affected disadvantaged communities compared to more advantaged areas [17], [18]. By the spring and summer of 2020, evidence emerged showing that disadvantaged neighborhood was linked to higher COVID-19 prevalence in various regions across the United States [19], [20]. In Chicago, Black and Hispanic residents have been disproportionately impacted. By the end of the first wave in 2020, Black residents accounted for 43% of COVID-19 deaths, even though they comprised only 29% of the city’s population. Similarly, Hispanic residents represented 48% of COVID-19 cases, despite also making up 29% of Chicago’s population [21]. Previous studies have also identified a spatial correlation between the percentage of Black residents and the number of COVID-19 deaths within Chicago neighborhoods [22], [23]. After the approval of the COVID-19 vaccines for emergency use by the US Food and Drug Administration (FDA), the goal across the country was to make sure that racial inequalities in COVID-19 outcomes were reduced. However, in many large cities, it was often the wealthier, predominantly White neighborhoods that got the vaccines first, instead of the communities that were most affected by the virus [24].

The University of Illinois System’s SHIELD Illinois (also called SHIELD) provided the cutting-edge saliva-based COVID-19 test to K–12 schools, colleges, universities, businesses, and the public throughout Illinois. Testing for SHIELD started in the Fall of 2020 and expanded quickly. In Fall 2020, SHIELD processed less than 5,000 tests; by May 2021, it processed 85,500 tests; by January 2022, it processed slightly under 900,000 tests. In May 2022, SHIELD cleared the 6-million-test level; in February 2023, it surpassed the 7-million-test threshold [25]. Saidani et al., (2021) [26] utilized SHIELD data to determine the optimal number of machines and operators required for different workstations, taking into account the available resources and the daily sample testing rate. Holman et al., (2023) [27] also leveraged SHIELD data to explore COVID-19 transmission in early care and education (ECE) settings through the implementation of a Test to Stay (TTS) strategy. Their findings revealed that transmission rates were low in ECE facilities during the study period. Moreover, serial testing after COVID-19 exposure among children and staff proved to be an effective strategy, enabling children to continue attending in-person and allowing parents to avoid missing workdays. Ivanov et al., (2023) [28] examined the effects of two different enrollment policies on testing and positivity rates using data from 259 schools in Illinois. Their results indicated a 42.6% higher testing rate and a 33.1% lower positivity rate in schools that adopted an opt-out policy. If all schools had implemented this policy, it could have prevented 20% of the total lost school days.

While the program has successfully increased testing rates across Illinois, its effectiveness in improving COVID-19 outcomes in disadvantaged communities remains unclear. The program has amassed extensive data on testing, encompassing the number and types of tests conducted, test results, and demographic information of those tested. This presents a unique opportunity to gain a comprehensive understanding of the impact of SHIELD Illinois on the health of disadvantaged communities in Chicago, especially when combined with data from the Chicago Department of Public Health and Electronic Health Records.

In this paper, we evaluate the relation between the (effective) number of SHIELD test centers on COVID-19 ICU admission rates across the different COVID-19 waves (i.e., Alpha, Delta, and Omicron). The Beta and Gamma COVID-19 waves are not taken into account because of the small number of patients involved [29]. We further analyze how factors like the socioeconomic status of different zip codes influence the effect of the number of SHIELD centers on ICU admissions. We particularly focus on a large academic hospital that serves a diverse population with highly different socioeconomic statuses in the western suburbs of Chicago. By addressing this aim, our study provides insight for public health officials to make more informed decisions to mitigate the impact of future pandemics.

**Methods**

**Study Design and Population**

This cohort study was a secondary analysis using deidentified data from the Loyola University Chicago ICU Emergency Health Record (EHR) system and the SHIELD Illinois Testing Program. The study was approved by the Institutional Review Board (IRB) of Loyola University Chicago.

We used datasets from the ICU at Loyola University Chicago and SHIELD testing data covering January 2020 to December 2023. Figure 1 illustrates the data filtration process used to refine the ICU dataset for the study, focusing on COVID-19 ICU admission rates. The process began with an initial dataset comprising ICU admissions from 585 zip codes collected between 2020 and 2023. From this dataset, the top 25% of zip codes with the highest frequency of patients served by Loyola Hospital were selected, reducing the dataset to 147 zip codes and concentrating on the areas most impacted by ICU admissions at Loyola (Figure 2). This strategic selection allowed us to concentrate on the areas most significantly impacted by ICU admissions at Loyola, thereby enhancing the robustness and reliability of our analysis of COVID-19 ICU admission rates. We chose these zip codes for two main reasons. First, these zip codes represent the areas most impacted by ICU admissions at Loyola, which provides a more robust and reliable dataset for analyzing COVID-19 ICU admission rates. Second, selecting the top 25% helps to reduce noise in the dataset by excluding zip codes with lower patient volumes, where the data might be less representative of broader trends. The next step involved filtering the dataset to include only COVID-19 patients, excluding non-COVID-19 patients based on COVID-19 ICD-10 codes (Table 1), standardized codes used to identify and classify COVID-19 cases. The final dataset included only COVID-19 patients from the 147 selected zip codes, spanning the same 2020-2023 timeframe. This refined dataset was then used for further analysis in the study.

A flowchart of datasets

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**Figure 1**: Data Filtration Diagram

**Table :** ICD-10 codes related to COVID-19

|  |  |
| --- | --- |
| COVID-19-relatedICD-10 code | Description |
| Z11.52 [30], [31] | Contact with and (suspected) exposure to COVID-19 |
| M35.81 [30], [32], [33] | Multisystem Inflammatory Syndrome (MIS) |
| J12.82 [30], [31] | Pneumonia due to Coronavirus disease 2019 |
| U07.1 [30], [31][32], [33], [34], [35], [36] | COVID-19 |
| U09.9 [32], [33] | Post-COVID-19 condition, unspecified |
| B97.29 [35], [36] | Other Coronavirus as the cause of disease classified elsewhere |
| J20.8 [36] | Acute bronchitis confirmed as due to COVID-19 |
| J22 [36] | Lower or acute respiratory infection due to COVID-19 |
| J98.8 [36] | Respiratory infection due to COVID-19 |
| J80 [36] | Acute Respiratory Distress Syndrome (ARDS) due to COVID-19 |

A map of a city

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**Figure 2:** Distribution of 147 zip codes with COVID-19 patients frequently served by Loyola hospital

The dataset comprised various variables essential for analyzing the impact of SHIELD test centers on COVID-19 ICU admissions rates across different zip codes. Below is a brief description of each variable included in the dataset:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Type | Class | Description | Mean | SD |
| COVID-19 ICU admission rate | Dependent | Continuous | The rate of ICU admission for COVID-19 per zip code, adjusted for population size. It is calculated by dividing the total COVID-19 ICU admissions by the zip code’s population and multiplying by 100,000 to standardize the rate per 100,000 people. | 0.044 | 0.091 |
|  |  |  |  |  |  |
| Zip Code | Independent | Categorical | 147 unique zip codes across Illinois, where Loyola University Chicago Hospital frequently treated COVID-19 patients |  |  |
|  |  |  |  |  |  |
| Total COVID-19 ICU admission per zip code per month | Independent | Continuous | total number of COVID-19 ICU admissions recorded each month for each zip code | 1.152 | 1.961 |
|  |  |  |  |  |  |
| Zip code population | Independent | Continuous | The population of each zip code | 35,432.58 | 20,722.64 |
|  |  |  |  |  |  |
| Effective number of SHIELD test centers | Independent | Continuous | The effective number of testing sites actively serving each zip code | 1.59 | 2.676 |
|  |  |  |  |  |  |
| Area Deprivation Index (ADI) | Independent | Categorical | The ADI score for each zip codes |  |  |

The ADI score categorizes zip codes into Low Disadvantaged and High Disadvantaged [37]. We consider Low Disadvantaged to be scores 1 through 4 (*N = 86*) and More Disadvantaged to be scores 5 through 9 (*N = 61*) based on socioeconomic factors. This variable explores disparities in ICU admissions and the impact of SHIELD centers in different socioeconomic contexts.

**Statistical Analysis**

We employed a linear mixed-effects regression model to investigate the association between the effective number of SHIELD test centers and the COVID-19 ICU admission rate. We focused on data from March 2021 to June 2021 for the Alpha wave, August 2021 to November 2021 for the Delta wave, similar to [15], and December 2021 to March 2022 for the Omicron wave, similar to [16]. The model included fixed effects such as the effective number of SHIELD centers per zip code per month and the ADI category. We incorporated a zip code-level random intercept to account for the monthly COVID-19 ICU admission rate clustering.

Additionally, we conducted robustness checks using lag analysis to assess the impact of SHIELD testing on the COVID-19 ICU admission rate across different waves. Specifically, we examined the effects with two-month lags to determine whether the timing of testing influenced subsequent COVID-19 ICU admissions.

All analyses were conducted using R statistical software version 2024.04.1 (R Project for Statistical Computing). The data analysis period spanned from March 1, 2024, to August 9, 2024.

**Results**

We examined the overall trends in the COVID-19 ICU admission rate and the availability of SHIELD test centers across all zip codes over the study period. This preliminary analysis provides insight into how both the COVID-19 ICU admissions rate and the effective number of test centers have evolved during the different COVID-19 waves. Figure 3 demonstrates the relationship between the average effective number of SHIELD test centers and the average COVID-19 ICU admission rates across different zip codes over time, categorized by their level of deprivation using the ADI. The green bars represent the average effective number of SHIELD test centers in less disadvantaged areas, while the orange bars indicate the same in more disadvantaged areas. The green and orange lines track the average COVID-19 ICU admission rates in less and more disadvantaged areas. The data reveals that during the pandemic’s peaks, specifically the Delta and Omicron waves, the effective number of SHIELD test centers increased significantly in both more and less disadvantaged areas. However, less disadvantaged areas consistently had a higher effective number of test centers throughout the observed period. Despite this, the COVID-19 ICU admission rates were generally higher in more disadvantaged zip codes, particularly during the Delta and Omicron waves. This trend suggests that more disadvantaged areas experienced a greater burden of severe COVID-19 cases, even as the number of SHIELD centers increased.

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**Figure 3:** Trends in COVID-19 ICU admission rates and effective number of SHIELD test center across zip codes over time

**Linear Mixed-Effect Regression Model**

Table 2 summarizes regression models examining the relationship between the effective number of SHIELD test centers and COVID-19 ICU admission rates during the Alpha, Delta, and Omicron waves. During the Delta wave, model 2 presents a positive and statistically significant estimate () for the more disadvantaged ADI. This suggests that these zip codes experienced higher COVID-19 ICU admission rates, reflecting a socioeconomic disparity in the burden of severe COVID-19 cases. For the Omicron wave, model 2 shows a positive and statistically significant estimate ( , ) indicating that more disadvantaged zip codes experienced higher COVID-19 ICU admission rates than less disadvantaged areas. Additionally, model 3 reveals that an increase in the effective number of SHIELD centers in more disadvantaged ADI areas is associated with a 0.5% reduction in the COVID-19 ICU admission rate (*p < 0.1*). Our data indicates that the average COVID-19 ICU admission rate in more disadvantaged zip codes is currently 6.33%. Therefore, enhancing the effectiveness of SHIELD centers by one unit would reduce the average COVID-19 ICU admission rate to 5.83% in these areas.

**Table 2**: Impact of SHIELD test centers and ADI on COVID-19 ICU admission rates

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Dependent Variable: COVID-19 ICU Admission Rate | | | | | | | | |
| independent Variable | Model 1  (Alpha) | Model 1  (Delta) | Model 1  (Omicron) | Model 2  (Alpha) | Model 2  (Delta) | Model 2  (Omicron) | Model 3  (Alpha) | Model 3  (Delta) | Model 3  (Omicron) |
| Effective Number of SHIELD Centers | -0.00542 (0.00542) | 0.00004 (0.00088) | -0.00249 (0.00165) |  |  |  |  |  |  |
| ADI (High Disadvantaged) |  |  |  | 0.00873 (0.00839) | 0.01609**\*** (0.00935) | 0.02076**\*** (0.01259) |  |  |  |
| Effective Number of SHIELD Centers\*ADI (High Disadvantaged) |  |  |  |  |  |  | 0.00408 (0.01162) | -0.00247 (0.00199) | -0.00594\* (0.00331) |
|  |  |  |  |  |  |  |  |  |  |
| Number of observations | 573 | 588 | 588 | 573 | 588 | 588 | 573 | 588 | 588 |
| Mean of the dependent variable in control group | 0.031 | 0.041 | 0.047 | 0.031 | 0.041 | 0.047 | 0.031 | 0.041 | 0.047 |
| Conditional R squared | 0.599 | 0.6 | 0.76 | 0.598 | 0.601 | 0.76 | 0.601 | 0.599 | 0.76 |
| Intraclass Correlation Coefficient (ICC) | 0.6 | 0.6 | 0.76 | 0.6 | 0.6 | 0.76 | 0.6 | 0.59 | 0.76 |
| *NOTE*: \*\*\*p<0.01, \*\*p<0.05, \*p<0.1 | | | | | | | | | |

Table 3 displays the findings of a regression analysis that investigates the influence of SHIELD test centers and ADI on COVID-19 ICU admission rates with a two-month delay. During the Delta wave, model 1 presents a negative and statistically significant estimate (, *p* < 0.1), indicating a significant reduction in the COVID-19 ICU admission rate two months after an increase in the effective number of SHIELD test centers. The data shows that the average COVID-19 ICU admission rate during the Delta wave is currently 4.14%. Therefore, improving the effectiveness of SHIELD centers by one unit would reduce the average COVID-19 ICU admission rate to 3.94% during two-month post-testing during this wave. Also, model 2 shows a positive and statistically significant estimate (, *p* < 0.1) for the more disadvantaged zip codes, suggesting that these areas experienced significantly higher COVID-19 ICU admission rates two months after testing. In the Omicron wave, model 2 shows a positive and statistically significant estimate (, *p* < 0.1) for the more disadvantaged zip codes, suggesting that these experienced significantly higher COVID-19 ICU admission rates two months after testing. Also, model 3 presents a negative estimate (, *p* < 0.1) for the interaction between the effective number of SHIELD test centers and more disadvantaged zip codes, suggesting a one-unit increase of SHIELD test centers in these areas would reduce the COVID-19 ICU admission rate from 6.33% to 5.66% two months after testing.

**Table 3**: Impact of SHIELD test centers and ADI on COVID-19 ICU admission rates (two-month lag)

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Dependent Variable: COVID-19 ICU Admission Rate | | | | | | | | |
| independent Variable | Model 1  (Alpha) | Model 1  (Delta) | Model 1  (Omicron) | Model 2  (Alpha) | Model 2  (Delta) | Model 2  (Omicron) | Model 3  (Alpha) | Model 3  (Delta) | Model 3  (Omicron) |
| Effective Number of SHIELD Centers | -0.00154 (0.00314) | -0.00199**\*** (0.00114) | -0.00236 (0.00158) |  |  |  |  |  |  |
| ADI (High Disadvantaged) |  |  |  | 0.00885 (0.00840) | 0.01609**\*** (0.00935) | 0.02076**\*** (0.01259) |  |  |  |
| Effective Number of SHIELD Centers\*ADI (High Disadvantaged) |  |  |  |  |  |  | -0.00806 (0.00713) | -0.00313 (0.00230) | -0.00678\*\* (0.00323) |
|  |  |  |  |  |  |  |  |  |  |
| Number of observations | 570 | 588 | 588 | 570 | 588 | 588 | 570 | 588 | 588 |
| Mean of the dependent variable in control group | 0.03 | 0.04 | 0.04 | 0.03 | 0.04 | 0.04 | 0.03 | 0.04 | 0.04 |
| Conditional R squared | 0.59 | 0.59 | 0.76 | 0.59 | 0.60 | 0.76 | 0.59 | 0.59 | 0.77 |
| Intraclass Correlation Coefficient (ICC) | 0.59 | 0.59 | 0.76 | 0.59 | 0.60 | 0.76 | 0.60 | 0.59 | 0.76 |
| *NOTE*: \*\*\*p<0.01, \*\*p<0.05, \*p<0.1 | | | | | | | | | |

**Discussion and Conclusion**

In this study, the total number of SHIELD centers operating in each zip code each month was computed. However, it could be misleading, as it may not accurately represent how many of these centers effectively served the zip codes in which they were located. Thus, we considered the effective number of SHIELD centers that served the zip code instead of the number of SHIELD centers that were located in this zip code. To calculate the effective number of SHIELD test centers each month, we determined the proportion of samples from each center and then aggregated these proportions to find the effective number of SHIELD test centers per zip code. Figure 4 compares the average number of SHIELD test centers and the average effective number of SHIELD test centers across all zip codes over time. The root mean square error (RMSE) between them is 0.94, indicating a close alignment between these two metrics. While some variations exist, this small RMSE suggests that the centers were generally effective in their operations relative to their number.

A graph showing the value of a wave

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**Figure 4:** Trends of SHIELD test centers and effective number of SHIELD centers over time for all zip codes

The results of this study highlight the critical role that the SHIELD testing program played in managing the COVID-19 pandemic, with particular emphasis on the proportion of these centers that were actively serving communities. While the overall number of SHIELD test centers increased during major waves of the pandemic, the proportion of centers that effectively served their respective zip codes significantly reduced the COVID-19 ICU admission rate.

During the Alpha and Delta waves, the effective number of SHIELD test centers alone did not significantly lower the COVID-19 ICU admission rate. However, during the Omicron wave, the results revealed that when a higher proportion of SHIELD centers actively served their communities, particularly in more disadvantaged areas, there was a statistically significant reduction in COVID-19 ICU admission rate. This provides evidence for the significant impact of the effective number of testing centers on mitigating severe COVID-19 outcomes. The lag analysis further supports this conclusion, showing that an increase in the effective number of SHIELD centers led to sustained reductions in COVID-19 ICU admission rates over time, particularly in socio-economically disadvantaged areas during the Omicron wave. This underscores the importance of maintaining the number of testing centers and ensuring that these centers are strategically deployed and effectively utilized to meet the evolving demands of the pandemic.

In summary, these findings suggest that the success of the SHIELD testing program depended not just on the number of testing centers but on their effectiveness, specifically how well they are strategically placed in areas where they are most needed, based on factors like socio-economic conditions and how efficiently they operate to maximize their impact. This strategic deployment and effective utilization are necessary to ensure that all communities, especially those that are more disadvantaged, have adequate access to testing resources, which is vital for controlling the spread of the virus and reducing severe outcomes.

Future public health strategies should optimize the deployment and operation of testing centers, particularly in vulnerable communities, to maximize their impact on reducing severe health outcomes during a pandemic.

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