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

**Abstract**

This study underscores the pivotal role of the SHIELD testing program in managing the COVID-19 pandemic, particularly through the concept of the “effective number” of test centers, those actively serving their communities. While the overall number of SHIELD test centers increased during major pandemic waves, the proportion of these centers effectively serving their respective zip codes significantly impacted the reduction of COVID-19 ICU admission rates. During the Alpha and Delta waves, the mere presence of SHIELD test centers did not markedly lower COVID-19 ICU admission rates. However, during the Omicron wave, a higher proportion of effectively serving centers, especially in more disadvantaged areas, was associated with a statistically significant reduction in COVID-19 ICU admission rates. The lag analysis further revealed that increases in the effective number of SHIELD test centers led to sustained decreases in COVID-19 ICU admission rates over time, particularly in socioeconomically disadvantaged communities. These findings highlight the necessity of maintaining the number of testing centers and ensuring their strategic deployment and efficient operation to meet the evolving demands of the pandemic. The success of the SHIELD program hinged on the effective placement of centers in areas most in need, which is vital for controlling the virus’s spread and reducing severe outcomes. This study provides insight for public health officials to make more informed decisions in mitigating the outcome of future pandemics.

**Background**

The COVID-19 pandemic demonstrated a wide range of severity, from mild to critical cases, resulting in over 7 million deaths globally and frequent ICU admissions, with nearly one-third of hospitalized adults requiring intensive care. [1], [2], [3], [4], [5], [6]. The emergence of new SARS-CoV-2 variants, including Alpha, Delta, and Omicron, complicated the management of COVID-19 [7] [8] [9] [10] [8] [11], [12]. Delta, originating in India, was the most severe, leading to higher rates of infection, hospitalization, and death, especially among the unvaccinated [13] [10] [14] [8], while Omicron spread rapidly but caused less severe illness [15], [16].

The COVID-19 pandemic has disproportionately affected disadvantaged communities [17], [18], [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 COVID-19 vaccines were approved 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.

The program has amassed extensive data on testing, encompassing the number and types of tests conducted, test results, and demographic information of those tested. While the program has successfully increased testing rates across Illinois, its contribution in promoting health equity remains unclear. This presents valuable opportunity to explore SHIELD Illinois' impact 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 availability 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 the impact of the geospatial determinants of health factors, including the zip code level's socioeconomic status, on the availability 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 Emergency Health Record (EHR) data from a major hospital in Chicago’s west suburbs and the SHIELD Illinois Testing Program. The study was approved by the Institutional Review Board (IRB) of Loyola University Chicago. We use datasets from the ICU at Loyola University Medical Center (LUMC) 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. The initial dataset included ICU admissions from 585 zip codes between 2020 and 2023. To narrow the scope and enhance the relevance of the analysis, we selected the top 25% of zip codes with the highest number of ICU admissions at LUMC, yielding a subset of 147 zip codes. This subset, shown in Figure 2, was chosen because these areas are predominantly served by LUMC which enables a more reliable assessment of the SHIELD program's impact on ICU admissions. Furthermore, we filtered the dataset to include only COVID-19 patients, identified using standardized ICD-10 codes for COVID-19 (Table 1). This step excluded non-COVID patients, resulting in a final dataset consisting solely of COVID-19 cases from the 147 selected zip codes, covering the same 2020-2023 period. 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-related ICD-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  Description automatically generated | A map with red and blue squares  Description automatically generated |
| 1. Selected Zip Codes in the Chicagoland Area and Surrounding Regions | 1. ADI Score Classification of Zip Codes in the Chicagoland Area |

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

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 LUMC 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 Area Deprivation Index (ADI) score categorizes zip codes into Low Disadvantaged and High Disadvantaged [37]. We consider Low Disadvantaged to be scores 1 through 4 and More Disadvantaged to be scores 5 through 9. 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, categorized by their level of deprivation using the ADI. 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 SHIELD test center across zip codes over time. 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.

**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

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **Predictors** | **Estimates** | **Significance Level** |
| **Alpha Wave** | | | |
| **1** | Effective Number of Test Centers | -0.00542  (SE) |  |
| **2** | ADI (More Disadvantaged) | 0.00873 |  |
| **3** | Effective Number of Test Centers\*ADI (More Disadvantaged) | 0.00403 |  |
|  |  |  |  |
| **Delta Wave** | | | |
|  | | | |
| **1** | Effective Number of Test Centers | 0.00004 |  |
| **2** | ADI (More Disadvantaged) | 0.01622 | **\*** |
| **3** | Effective Number of Test Centers\*ADI (More Disadvantaged) | -0.00247 |  |
|  |  |  |  |
| **Omicron Wave** | | | |
|  | | | |
| **1** | Effective Number of Test Centers | -0.00249 |  |
| **2** | ADI (More Disadvantaged) | 0.02097 | **\*** |
| **3** | Effective Number of Test Centers\*ADI (More Disadvantaged) | -0.00594 | **\*** |

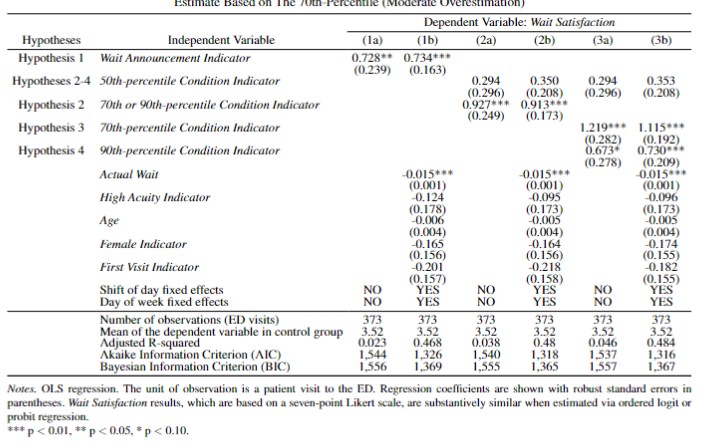
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Table 3 presents the regression analysis examining the impact of SHIELD test centers and ADI on COVID-19 ICU admission rates with a one-month lag. This lag analysis aims to determine how COVID-19 testing influences COVID-19 ICU admission rates one month later, considering different COVID-19 waves. During the Delta wave, model 2 presents a positive and statistically significant estimate (1.622%, *p* < 0.1) for the more disadvantaged zip codes, indicating that these areas experienced significantly higher COVID-19 ICU admission rates one month after testing.

In the Omicron wave, model 1 indicates a negative and statistically significant estimate (-0.287%, *p* < 0.1), suggesting a significant reduction in COVID-19 ICU admissions one month after an increase in the effective number of SHIELD test centers. With the current average COVID-19 ICU admission rate at 4.77%, this decrease would lower the rate to 4.49% one-month post-testing. Additionally, Model 2 presents a positive and statistically significant estimate (2.097%, *p* < 0.1) for the more disadvantaged zip codes, indicating that these areas experienced significantly higher COVID-19 ICU admission rates one month after testing.

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

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **Predictors** | **Estimates** | **Significance Level** |
| **Alpha Wave** | | | |
| **1** | Effective Number of Test Centers | 0.00251 |  |
| **2** | ADI (More Disadvantaged) | 0.00885 |  |
| **3** | Effective Number of Test Centers:ADI (More Disadvantaged) | -0.00083 |  |
|  |  |  |  |
| **Delta Wave** | | | |
|  | | | |
| **1** | Effective Number of Test Centers | -0.00149 |  |
| **2** | ADI (More Disadvantaged) | 0.01622 | **\*** |
| **3** | Effective Number of Test Centers:ADI (More Disadvantaged) | -0.00259 |  |
|  |  |  |  |
| **Omicron Wave** | | | |
|  | | | |
| **1** | Effective Number of Test Centers | -0.00287 | **\*** |
| **2** | ADI (More Disadvantaged) | 0.02097 | **\*** |
| **3** | Effective Number of Test Centers:ADI (More Disadvantaged) | -0.00447 |  |

Table 4 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 (-0.199%, *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% two-month post-testing during this wave. Also, model 2 shows a positive and statistically significant estimate (1.622%, *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 (2.097, *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 (-0.678%, *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 4**: Impact of SHIELD test centers and ADI on COVID-19 ICU admission rates (two-month lag)

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **Predictors** | **Estimates** | **Significance Level** |
| **Alpha Wave** | | | |
|  |  |  |  |
| **1** | Effective Number of Test Centers | -0.00154 |  |
| **2** | ADI (More Disadvantaged) | 0.00885 |  |
| **3** | Effective Number of Test Centers:ADI (More Disadvantaged) | -0.00806 |  |
|  |  |  |  |
| **Delta Wave** | | | |
|  | | | |
| **1** | Effective Number of Test Centers | -0.00199 | **\*** |
| **2** | ADI (More Disadvantaged) | 0.01622 | **\*** |
| **3** | Effective Number of Test Centers:ADI (More Disadvantaged) | -0.00313 |  |
|  |  |  |  |
| **Omicron Wave** | | | |
|  | | | |
| **1** | Effective Number of Test Centers | -0.00236 |  |
| **2** | ADI (More Disadvantaged) | 0.02097 | **\*** |
| **3** | Effective Number of Test Centers:ADI (More Disadvantaged) | -0.00678 | \* |

**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 3 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 3:** 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, the “effective number” of SHIELD test centers. 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 an evidence for the significant impactof the 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. 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, the 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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