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

Alireza Kasaie, PhD1, Amy Wozniak2, Fatir Ihsan3, Michael T. Saban, MS1, William F. Parker, MD, PhD4 5 6, Milda Saunders M.D., M.P.H4, Sina Ansari, PhD3, Mohammad Samie Tootooni, PhD1\*,

1Parkinson School of Health Sciences and Public Health, Loyola University Chicago, Maywood, IL 60153, USA; 2Clinical Research Office, Loyola University Chicago, Maywood, IL 60153, USA; 3Driehaus College of Business, DePaul University, Chicago, IL 60604, USA; 4Department of Medicine, University of Chicago, Chicago, IL, 60637 USA; 5MacLean Center for ClinicalMedical Ethics, University of Chicago, Chicago, IL 60637, USA; 6Department of Public Health Sciences, University of Chicago, Chicago, IL, 60637 USA

\*Corresponding Author: Mohammad Samie Tootooni, PhD

Parkinson School of Health Sciences and Public Health

Loyola University Chicago

2160 S. First Ave

Maywood, IL, 60153

708 216 9181

Email: [mtootooni@luc.edu](mailto:mtootooni@luc.edu)

**Abstract**

**Background**

The COVID-19 pandemic, particularly with variants Alpha, Delta, and Omicron, presented major challenges in managing severe cases from 2021 to 2023. Disadvantaged communities were disproportionately affected, especially during the Delta and Omicron waves. SHIELD Illinois, a statewide saliva-based testing program, aimed to increase testing access, but its impact on COVID-19 outcomes in these communities remains unclear. This study investigates the relationship between the effective number of SHIELD test centers and COVID-19 ICU admission rates, focusing on the role of socioeconomic factors across zip codes in Chicago’s western suburbs.

**Methods**

We conducted a secondary analysis using data from Loyola University Chicago’s ICU EHR system and the SHIELD Illinois Testing Program, covering the Alpha (March–June 2021), Delta (August–November 2021), and Omicron (December 2021–March 2022) waves. A linear mixed-effects regression model assessed the relationship between SHIELD test center availability and ICU admissions, adjusting for SHIELD center density and area deprivation index (ADI) scores.

**Results**

Despite the increased number of SHIELD centers, disadvantaged areas consistently had higher ICU admission rates, particularly during the Delta and Omicron waves. However, increasing SHIELD centers during Omicron was associated with a reduction in ICU admissions. A two-month lag analysis further confirmed that enhanced SHIELD center effectiveness led to lower ICU rates, particularly in disadvantaged communities.

**Conclusion**

These findings highlight the importance of strategically deploying SHIELD test centers to reduce severe outcomes and ensure 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. [5] highlight that COVID-19 patients experience increased rates of hospitalization and intensive care unit (ICU) admissions. Supporting this observation, Kim et al. [6] find that among a sample of 2,491 adults hospitalized with confirmed COVID-19, nearly one-third need admission to the ICU.

The emergence of the Alpha, Delta, and Omicron variants significantly impacted the management of the COVID-19 pandemic. The Alpha variant, dominant in early 2021, was linked to higher hospitalization and ICU admission rates. However, the Delta variant, more transmissible and severe, led to a sharp increase in ICU admissions and deaths, particularly among unvaccinated populations. In contrast, while the Omicron variant spread more rapidly, it caused less severe illness and lower ICU admissions than Delta. Understanding the differing impacts of these variants is crucial for evaluating COVID-19 interventions and outcomes [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]. Understanding the factors that influence ICU admissions, including the role of interventions such as testing programs, is crucial, especially when considering the pandemic’s disproportionate impact on different communities.

The COVID-19 pandemic has disproportionately affected disadvantaged communities compared to more advantaged areas [17], [18]. As early as the spring and summer of 2020, evidence emerged showing that disadvantaged neighborhoods were linked to higher COVID-19 prevalence in various regions across the United States [19], [20]. Minority communities and individuals living in poverty experience a significantly higher share of COVID-19 cases and deaths [21], [22]. Previous research on health disparities has identified a connection between adverse health outcomes and low socioeconomic status, frequently measured using the area deprivation index (ADI) as a ranked indicator of geographic disadvantage [23], [24]. Despite this, little is known about COVID-19 testing programs' specific role in mitigating the burden of ICU admissions in socioeconomically disadvantaged areas. Understanding the importance of testing in such communities is critical, as it may help reduce the virus's spread and severity.

As the transmission of severe acute COVID-19 continues within the United States, ongoing attention focuses on the importance of testing to control and reduce its spread [25]. The importance of COVID testing extends far beyond simply diagnosing the infection. While it helps individuals determine whether they have the virus and what steps to take next (e.g., quarantine, isolation, or treatment), testing is also critical in understanding and managing the pandemic [26]. According to the National Institutes of Health (NIH) [27], COVID-19 testing is crucial for vulnerable populations and those in areas with high ADI scores, as it enables early detection and helps prevent the virus’s spread in communities that are disproportionately impacted by the pandemic. Testing programs targeting these areas can be essential in mitigating the adverse health outcomes related to COVID-19.

One such initiative is the University of Illinois System’s testing program, SHIELD Illinois, which provides a cutting-edge saliva-based COVID-19 test to K-12 schools, colleges, universities, businesses, and the public throughout Illinois. Initially, SHIELD focused on preserving lives by allowing businesses to stay open. As it expanded into schools, the program shifted towards ensuring students could remain in the classroom by maximizing access to testing and the number of students tested. A standout feature of the SHIELD program is its ability to provide schools with adequate test kits, with testing frequency limited to once or, in exceptional cases, twice per week. In Fall 2020, SHIELD processed less than 5,000 tests; by May 2021, it processed 85,500 tests; By January 2022, it had 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 [28]. 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 SHIELD Illinois's 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.

Several other studies have used data from SHIELD to analyze its effectiveness in addressing COVID-19. For instance, Saidani et al. [29] utilize SHIELD data to determine the optimal number of machines and operators required for different workstations, considering the available resources and the daily sample testing rate. Holman et al. [30] also leverage SHIELD data to explore COVID-19 transmission in early care and education (ECE) settings by implementing a Test-to-Stay (TTS) strategy. Their findings reveal that transmission rates are low in ECE facilities during the study period. Moreover, serial testing after COVID-19 exposure among children and staff proves an effective strategy, enabling children to continue attending in person and allowing parents to avoid missing workdays. Ivanov et al. [31] examine the effects of two different enrollment policies on testing and positivity rates using data from 259 schools in Illinois. Their results indicate 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, 20% of the lost school days could have been prevented. These examples highlight the versatility of SHIELD data in addressing various aspects of COVID-19 management. However, a detailed investigation of its impact on ICU admissions, particularly in socioeconomically disadvantaged areas, remains unexplored.

In this study, we employ a linear mixed-effects regression model to assess the relationship between the effective number of SHIELD test centers, X, and COVID-19 ICU admission rates, adjusting for fixed effects such as SHIELD center density and area deprivation index (ADI) score. To account for the timing of testing and ICU admissions, we perform a robustness check using a two-month lag analysis across different COVID-19 waves. Our findings reveal that, despite the increased number of SHIELD test centers, disadvantaged areas consistently experience higher ICU admission rates, particularly during the Delta and Omicron waves. However, the results indicate that increasing the number of SHIELD centers during the Omicron wave is associated with a reduction in ICU admissions in these areas. The lag analysis further supports that enhancing the effectiveness of SHIELD centers over time leads to lower ICU rates, with disadvantaged communities especially benefiting from these targeted interventions. These findings highlight the critical role of strategically deploying SHIELD test centers in socioeconomically disadvantaged areas to reduce severe COVID-19 outcomes and emphasize the importance of equitable resource allocation in future pandemic responses.

The remainder of this paper is structured as follows: Section 2 outlines the methodology used in the study, Section 3 presents the results, and Section 4 discusses the findings and concludes the study.

**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 Loyola University Chicago Institutional Review Board (IRB) approved the study.

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We used datasets from the ICU at Loyola University Chicago and SHIELD testing data covering January 2020 to December 2023. To ensure a relevant and accurate analysis of COVID-19 ICU outcomes, a filtration process was applied to the original ICU dataset. This filtration was necessary to focus on the zip codes most affected by ICU admissions, thereby improving the reliability of the analysis. The initial dataset, which contained ICU admissions from 585 zip codes collected between 2020 and 2023, was refined by selecting the top 25% of zip codes with the highest frequency of patients served by Loyola Hospital. Figure 1 illustrates the data filtration process used to refine the ICU dataset, focusing on COVID-19 ICU admission rates. This reduction to 147 zip codes allowed for a more targeted examination of the areas that experienced the greatest impact from ICU admissions during the pandemic (Figure 2). 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. This strategic selection allowed us to focus on the areas that were most significantly affected by ICU admissions at Loyola, thereby enhancing the robustness and reliability of our analysis of COVID-19 ICU admission rates. 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 (see **Appendix 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 patient data

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**Figure 1**: Data Filtration Diagram

A map with different colored areas

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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 admission rates across different zip codes, including ADI, which maps the relative socioeconomic status of neighborhoods. This integration allows for a deeper understanding of how socioeconomic factors influence the effectiveness of SHIELD interventions. This index uses publicly available data to assess factors such as income, education, employment, and housing quality. The ADI ranks neighborhoods by comparing their socioeconomic conditions to state and national averages, with higher rankings indicating greater disadvantage. This tool helps identify neighborhoods facing significant socioeconomic challenges, making them potential priorities for future investment and support initiatives [39], [40]. We consider Lowly Disadvantaged zip codes to be scores 1 through 4 (*N = 86*) and Highly Disadvantaged zip codes to be scores 5 through 9 (*N = 61*) based on socioeconomic factors and similar to the literature [39]. This variable explores disparities in ICU admissions and the impact of SHIELD centers in different socioeconomic contexts. In this study, we use the effective number of SHIELD test centers as the dependent variable, defined as the proportion of a test center’s service to a given area. Although these centers are located in schools within specific zip codes, students often attend schools outside their residential areas. Since students represent their home communities, it is crucial to account for the effective number of centers to reflect their broader reach across adjacent regions. To calculate the effective number of SHIELD test centers each month, we determined the proportion of samples from each center and aggregated these proportions to find the effective number of SHIELD test centers per zip code (see **Appendix 2**). Furthermore, we use the COVID-19 ICU admission rate as the dependent variable in this study, calculated as the number of ICU admissions per zip code per month, normalized by the population of each zip code, and multiplied by 1,000 for scaling. This measure allows us to standardize the ICU admission data across zip codes of varying population sizes (see **Appendix 3**). Table 1 provides a brief description of each variable included in the dataset.

**Table 1:** Variable description

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 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 |
|  |  |  |  |  |  |
| State ADI | Independent | Categorical | The ADI score for each zip code | 4.27 | 1.82 |
| *NOTE*: Several control variables were considered to account for factors that may also influence COVID-19 ICU admission rates. These include population density, gender distribution, age distribution, racial and ethnic composition, pre-existing health conditions (such as diabetes and heart disease), insurance status, and marital status across different zip codes. | | | | | |

**Statistical Analyses**

In this study, 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 [41], and December 2021 to March 2022 for the Omicron wave [2]. The Beta and Gamma COVID-19 waves are not considered because of the small number of patients involved [42]. 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 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 [43]. All analyses were conducted using R statistical software version 2024.04.1, and 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 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 high and low-disadvantaged areas. However, low-disadvantaged areas consistently had a higher effective number of test centers throughout the observed period. One possible explanation could be the SHIELD program policy regarding the participants. According to SHIELD, participation in the program was voluntary, and school districts, including Chicago Public Schools, had the final decision on whether to engage in the program. Despite this, the COVID-19 ICU admission rates were generally higher in highly disadvantaged zip codes, particularly during the Delta and Omicron waves. This trend suggests that more disadvantaged areas experienced a more significant burden of severe COVID-19 cases, even as the number of SHIELD centers increased.

A graph of different colored lines

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**Figure 3:** Trends in COVID-19 ICU admission rates and effective number of SHIELD test centers 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. While none of the models indicate a significant impact of SHIELD test centers in disadvantaged areas during the Alpha wave, Model 2 during the Delta wave shows a positive and statistically significant effect () for areas with a higher 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 reduction in the COVID-19 admission rate (*p* < 0.1). Our data shows that the average COVID-19 ICU admission rate in highly disadvantaged zip codes is currently 0.063 among a population of 8,755,292. By increasing the effective number of SHIELD test centers by one unit, we estimate a reduction of approximately 51,774 ICU admissions in these areas, lowering the average ICU admission rate from 0.063 to 0.057.

**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) |  |  |  | -0.00853  (0.00957) | 0.00086  (0.00104) | 0.00030  (0.00217) |
| ADI (High Disadvantaged) |  |  |  | 0.00873 (0.00839) | 0.01609**\*** (0.00935) | 0.02076**\*** (0.01259) | 0.00833  (0.00883) | 0.02103\*\*  (0.01012) | 0.03842\*\*  (0.01652) |
| 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 the 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 | 0.60 | 0.76 | 0.59 | 0.60 | 0.76 | 0.60 | 0.59 | 0.76 |
| Intraclass Correlation Coefficient (ICC) | 0.60 | 0.60 | 0.76 | 0.60 | 0.60 | 0.76 | 0.60 | 0.59 | 0.76 |
| VIF (Effective Number of SHIELF Centers) | 3.04 | 1.47 | 1.78 | 3.04 | 1.47 | 1.78 | 3.04 | 1.47 | 1.78 |
| VIF (ADI) | 1.29 | 1.55 | 1.88 | 1.29 | 1.55 | 1.88 | 1.29 | 1.55 | 1.88 |
| VIF (Interaction Term) | 3.47 | 1.79 | 2.46 | 3.47 | 1.79 | 2.46 | 3.47 | 1.79 | 2.46 |
| *NOTE*: LMM regression. The model included fixed effects such as the effective number of SHIELD centers per zip code per month and the ADI category. The model included a random effect for zip code. The unit of observation is the number of zip codes that have patients in Loyola ICU. Regression coefficients are shown with robust standard errors in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1 | | | | | | | | | |

**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) |  |  |  | 0.00049  (0.00366) | -0.00034  (0.00154) | 0.00038  (0.00199) |
| ADI (High Disadvantaged) |  |  |  | 0.00885 (0.00840) | 0.01609**\*** (0.00935) | 0.02076**\*** (0.01259) | 0.01204  (0.00885) | 0.02384\*\*  (0.01178) | 0.04066\*\*  (0.01604) |
| 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 the 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 |
| VIF (Effective Number of SHIELF Centers) | 1.66 | 1.68 | 1.78 | 1.66 | 1.68 | 1.78 | 1.66 | 1.68 | 1.78 |
| VIF (ADI) | 1.33 | 1.88 | 1.82 | 1.33 | 1.88 | 1.82 | 1.33 | 1.88 | 1.82 |
| VIF (Interaction Term) | 2.04 | 2.24 | 2.46 | 2.04 | 2.24 | 2.46 | 2.04 | 2.24 | 2.46 |
| *NOTE*: LMM regression. The model included fixed effects such as the effective number of SHIELD centers per zip code per month and the ADI category. The model included a random effect for zip code. The unit of observation is the number of zip codes that have patients in Loyola ICU. Regression coefficients are shown with robust standard errors in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1 | | | | | | | | | |

**Discussion and Conclusion**

The results of this study highlight the critical role the SHIELD testing program plays in managing the COVID-19 pandemic, with particular emphasis on the proportion of testing centers actively serving communities. In this analysis, the total number of SHIELD centers operating in each zip code per month was calculated. However, relying solely on the total number of SHIELD centers could be misleading, as it does not account for whether these centers were actively utilized or accessible to the community. Thus, we considered the effective number of SHIELD centers serving each zip code, rather than the total number. Our results showed that the root mean square error (RMSE) between the average number of SHIELD test centers and the average effective number across all zip codes over time was 0.94, indicating a close alignment between these two metrics (see **Appendix 4**). While some variation exists, this small RMSE suggests that, in general, the centers were effective in serving their communities.

As the overall number of SHIELD test centers increased during major pandemic waves, the proportion of centers effectively serving their respective zip codes significantly reduced COVID-19 ICU admission rates. The LMM model results demonstrate the evolving impact of SHIELD test centers throughout the pandemic. During the Alpha wave, the presence of test centers did not notably reduce ICU admissions, likely because testing efforts were not yet fully optimized or widespread. However, by the Delta and Omicron waves, the data suggest that the effectiveness of these centers improved, particularly in disadvantaged areas with higher ADI scores. The significant positive association observed during the Delta and Omicron waves indicates that socioeconomically disadvantaged zip codes experienced disproportionately higher ICU admission rates, highlighting ongoing disparities in the pandemic's burden. Notably, the reduction in ICU admissions with an increase in the effective number of SHIELD test centers during the Omicron wave suggests that, once these centers actively served their communities, they played a critical role in mitigating severe outcomes. This finding underscores the importance of not just the availability of test centers but also their active utilization and accessibility in reducing COVID-19’s most severe effects, particularly in vulnerable populations.

The results from the lag analysis further illustrate the evolving impact of SHIELD test centers, especially when considering a two-month delay in their effect on COVID-19 ICU admissions. During the Alpha wave, the presence of SHIELD test centers did not significantly reduce ICU admissions in disadvantaged areas, likely because the testing infrastructure was still in its early stages and not fully optimized. By the Delta wave, however, an increase in the effective number of SHIELD test centers was associated with a significant reduction in ICU admissions two months later. This delayed effect suggests that enhanced testing efforts eventually played a critical role in reducing severe outcomes. Specifically, increasing the number of effective SHIELD test centers appears to have significantly eased the burden on healthcare systems during the Delta wave, underscoring the importance of sustained and targeted testing efforts. Despite this, disadvantaged zip codes continued to face disproportionately higher ICU admission rates, as reflected in the positive association found during both the Delta and Omicron waves. This highlights the persistent challenges faced by these communities, where broader socioeconomic barriers may have limited the immediate benefits of increased testing. Nonetheless, the reduction in ICU admissions associated with an increase in the effective number of SHIELD test centers during the Omicron wave, particularly in high-ADI areas, suggests that targeted testing interventions can make a substantial difference over time. These findings demonstrate that by strategically increasing testing in disadvantaged communities, significant reductions in severe outcomes can be achieved, even with a delayed effect.

This study has a few limitations that should be considered when interpreting the results. First, we used ICU data from only one hospital, which may limit the generalizability of our findings. Future studies should include data from multiple hospitals to better capture the broader impact of SHIELD test centers. Second, since the SHIELD Illinois testing program was conducted only in Illinois, we did not account for data from other states. Future research should consider testing programs across multiple states to provide more generalizable results and better evaluate the effectiveness of SHIELD Illinois within a wider context.

In summary, these findings indicate that the success of the SHIELD testing program was not solely determined by the number of testing centers but by their effectiveness in serving communities, particularly in areas of greatest need. Factors such as socioeconomic conditions and the strategic placement of test centers played a key role in maximizing their impact. Ensuring that disadvantaged communities had access to well-utilized and efficiently operated testing resources was crucial for controlling the spread of the virus and reducing severe health outcomes. Moving forward, public health strategies should focus on optimizing the placement and functionality of testing centers, especially in vulnerable areas, to enhance their effectiveness in mitigating severe outcomes during a pandemic. As part of this effort, our future research will focus on optimizing the location of SHIELD testing centers to maximize both testing coverage and equity in highly disadvantaged zip codes, ensuring that resources are deployed where they are most needed.

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**Appendix 1: ICD-10 codes related to COVID-19**

|  |  |
| --- | --- |
| COVID-19-relatedICD-10 code | Description |
| Z11.52 [32], [33] | Contact with and (suspected) exposure to COVID-19 |
| M35.81 [32], [34], [35] | Multisystem Inflammatory Syndrome (MIS) |
| J12.82 [32], [33] | Pneumonia due to Coronavirus disease 2019 |
| U07.1 [32], [33][34], [35], [36], [37], [38] | COVID-19 |
| U09.9 [34], [35] | Post-COVID-19 condition, unspecified |
| B97.29 [37], [38] | Other Coronavirus as the cause of disease classified elsewhere |
| J20.8 [38] | Acute bronchitis confirmed as due to COVID-19 |
| J22 [38] | Lower or acute respiratory infection due to COVID-19 |
| J98.8 [38] | Respiratory infection due to COVID-19 |
| J80 [38] | Acute Respiratory Distress Syndrome (ARDS) due to COVID-19 |

**Appendix 2: Quantifying the Effective Coverage of SHIELD Test Centers**

Where is the proportion of samples collected by test center from zip code in month

The effective number of SHIELD test centers serving zip code in month , denoted as , can be calculated by aggregating these proportions across all test centers:

**Appendix 3: Mathematical Calculation of COVID-19 ICU Admission Rate**

The COVID ICU admission rate for zip code during month , denoted as

This formula calculates the number of ICU admissions per 1,000 people for a given zip code in a given month

**Appendix 4: Trends of SHIELD test centers and effective number of SHIELD centers over time**

A graph showing the value of a wave

Description automatically generated with medium confidence

**Figure A.1:** Trends of SHIELD test centers and effective number of SHIELD centers over time for all zip codes