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

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1 **Abstract**

2 **Background**

3 The COVID-19 pandemic, particularly with variants Alpha, Delta, and Omicron, presented major challenges in

4 managing severe cases. Disadvantaged communities were disproportionately affected, especially during the Delta and

5 Omicron waves. SHIELD Illinois, a statewide saliva-based testing program, aimed to increase testing access, but its

6 impact on COVID-19 outcomes in these communities remains unclear. This study investigates the impact of SHIELD

7 test centers on the rate of COVID-19 admissions to intensive care units (ICUs) in the communities they serve, with a

8 particular focus on the socioeconomic factors of these communities in the greater Chicago area.

9 **Method**

10 We conducted a secondary analysis using data from the Electronic Health Record (EHR) system of a large quaternary

11 care medical center in a western Chicago suburb and the SHIELD Illinois Testing Program. The study covers the

12 Alpha (March–June 2021), Delta (August–November 2021), and Omicron (December 2021–March 2022) waves. A

13 linear mixed-effects regression model, along with robustness checks, was used to assess the relationship between

14 SHIELD test center availability and ICU admissions, adjusting for SHIELD center density and area deprivation index

15 scores.

16 **Result**

17 The expansion of SHIELD centers during the Omicron wave was strongly associated with a significant reduction in

18 COVID-19 ICU admissions in disadvantaged zip codes. Regression analyses indicated that although more deprived

19 areas initially experienced higher ICU admission rates, increasing the number of SHIELD centers during the Omicron

20 surge led to a 0.6% reduction in the incidence rate ratio, translating to a decrease of 0.38 ICU admissions per 1,000

21 population. Furthermore, lag analyses demonstrated that the enhanced effectiveness of SHIELD centers contributed

22 to even greater reductions in ICU admissions over time. This impact was particularly pronounced in disadvantaged

23 communities, where the IRR dropped by 0.7%, corresponding to a decrease of 0.45 ICU admissions per 1,000

24 population.

25 **Conclusion**

26 These findings highlighted the importance of strategically deploying SHIELD test centers to reduce severe outcomes

27 and ensure equitable healthcare responses in future pandemics.

28 **Keywords**

1 SHILED Illinois; COVID-19 ICU admission; Socioeconomic disparities; Linear mixed-effect model; Pandemic

2 response strategies

3 **Background**

4 The World Health Organization declared COVID-19 a pandemic on March 11, 2020, resulting in over 7

5 million deaths globally (1–3). COVID-19 symptoms range from mild to critical, with ICU admission rates

6 varying widely, from 5% to 32% globally (4–6). Among ICU patients, 99% require respiratory support, and

7 26% do not survive (7,8). These statistics highlight the importance of understanding ICU admission drivers

8 and examining the role of interventions, such as testing programs, in mitigating severe outcomes. Such

9 efforts must account for the dynamic nature of the pandemic, as variants like Alpha, Delta, and Omicron

10 have demonstrated varied impacts on ICU outcomes. The Alpha variant increased ICU rates by 2.72%,

11 while Delta caused surges in ICU admissions and deaths, especially among the unvaccinated, who were

12 five times more likely to be hospitalized and seven times more likely to die in areas like Chicago (9) (10).

13 Omicron, though more transmissible, led to milder disease, shorter hospital stays, and fewer ICU

14 admissions, particularly among vaccinated individuals (11–19).

15 The COVID-19 pandemic disproportionately impacted disadvantaged communities, with higher COVID-

16 19 prevalence and deaths driven by systemic inequities such as poverty, limited healthcare access,

17 segregation, and occupational risks (20–26). Studies show a strong link between COVID-19 outcomes and

18 the area deprivation index (ADI), a measure of social disadvantage (27–30). The National Institutes of

19 Health emphasizes the importance of testing in vulnerable populations and high-ADI communities to enable

20 early detection and curb the virus's spread in these disproportionately affected areas (31). Targeted testing

21 programs are essential for reducing adverse health outcomes in such populations.

22 One example is the University of Illinois System's SHIELD Illinois testing program, which provides

23 innovative saliva-based COVID-19 tests to K-12 schools, colleges, universities, businesses, and community

24 centers across Illinois (32). Initially, SHIELD focused on preserving lives by allowing businesses to stay

25 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 (33). 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 Record (EHR).

Recent studies have assessed the effectiveness of SHIELD Illinois in managing COVID-19, but its specific impact on ICU admissions, particularly in socioeconomically disadvantaged areas, remains underexplored. This study aims to address this gap by investigating the relationship between SHIELD test center availability and COVID-19 ICU admission rates, with a focus on the moderating role of socioeconomic factors. Additionally, we evaluate the effect of SHIELD test centers in reducing ICU admissions across different COVID-19 waves, particularly in disadvantaged communities. This study highlights the benefits of expanding test center access to reduce severe COVID-19 cases and underscores the importance of ensuring equitable resource distribution in future pandemics.

Methods

Study Design and Population

This cohort study was a secondary analysis using deidentified data from the EHR data of ICU patients at Loyola University Medical Center, and the SHIELD Illinois Testing Program. The Loyola University Chicago Institutional Review Board (IRB) approved the study.

Loyola University Medical Center (LUMC) is a regional academic health system and a nationally ranked quaternary care facility with 547 licensed beds, located in Chicago's western suburbs (34,35). LUMC's

extensive catchment area and the high number of ICU admissions make it an ideal representative for examining the effectiveness of SHIELD testing and its correlation with COVID-19 ICU outcomes.

We used datasets from the ICU at LUMC and the 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 dataset includes 29,779 patient visits from 585 zip codes across Illinois, providing a robust sample for analysis. The initial dataset was refined by selecting the top 25% of zip codes with the highest frequency of patients served by LUMC. 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, depicted in Figure 2, allowed for a more targeted examination of the areas that experienced the greatest impact from ICU admissions during the pandemic. Selecting the top 25% helps to reduce noise in the dataset by excluding zip codes with lower patient volumes at LUMC, 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 LUMC, thereby enhancing the robustness and reliability of our analysis of COVID-19 ICU admission rates. The next step involved refining the dataset to focus exclusively on patients treated for COVID-19, achieved by filtering out non-COVID-19 cases using the appropriate ICD-10 codes for COVID-19 diagnoses (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.
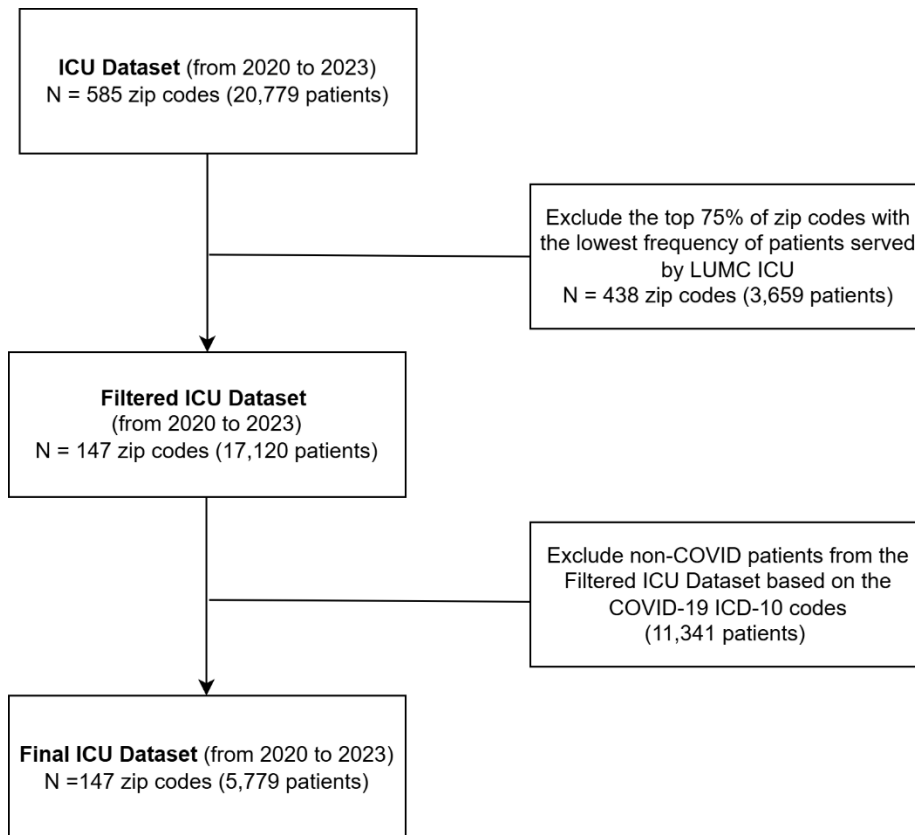
ICU Dataset (from 2020 to 2023)
N = 585 zip codes (20,779 patients)

Exclude the top 75% of zip codes with
the lowest frequency of patients served
by LUMC ICU
N = 438 zip codes (3,659 patients)

Filtered ICU Dataset
(from 2020 to 2023)
N = 147 zip codes (17,120 patients)

Exclude non-COVID patients from the
Filtered ICU Dataset based on the
COVID-19 ICD-10 codes
(11,341 patients)

Final ICU Dataset (from 2020 to 2023)
N =147 zip codes (5,779 patients)

1
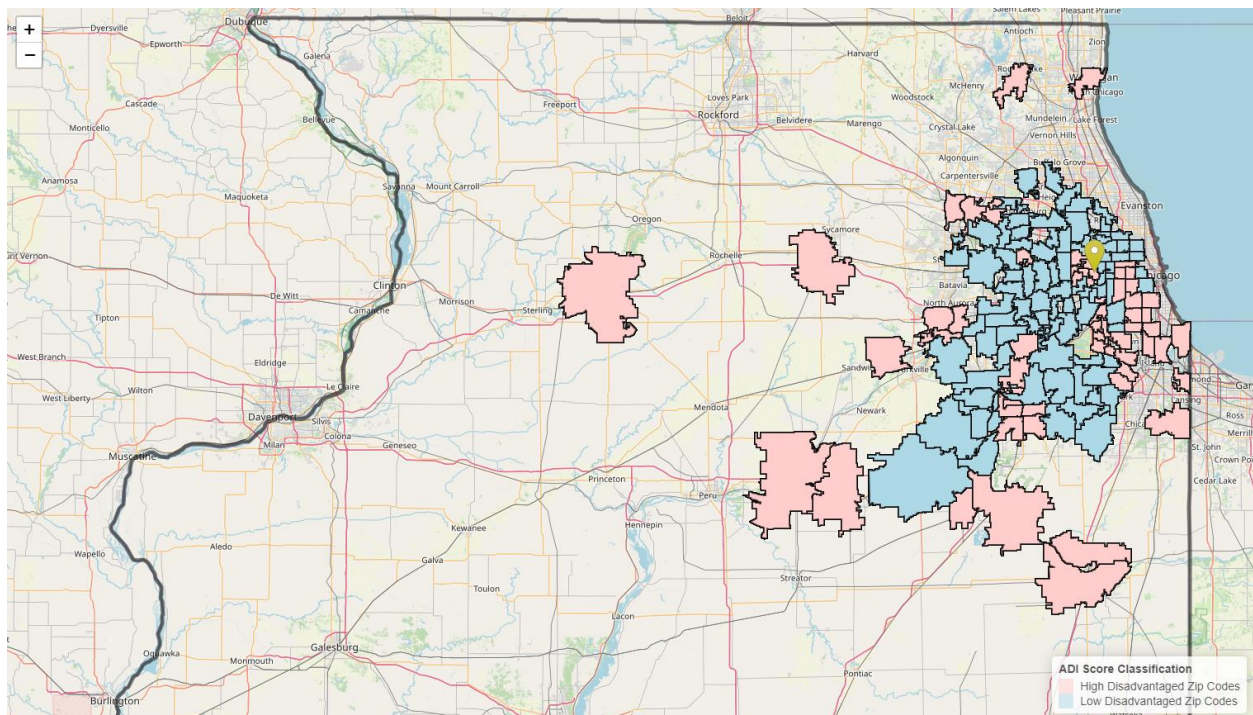
2 **Figure 1**: Data Exclusion Diagram

3

4 **Figure 2:** Distribution of 147 zip codes with COVID-19 patients frequently served by LUMC
5

Independent variables

Area deprivation index This index uses publicly available data to assess factors such as income, education, employment, and housing quality. ADI ranks neighborhoods by comparing their socioeconomic conditions to state and national averages, with higher rankings indicating greater disadvantage (36). This tool helps identify neighborhoods facing significant socioeconomic challenges, making them potential priorities for future investment and support initiatives (37,38). We consider low disadvantaged zip codes to be scores 1 through 4 ($N = 86$) and high disadvantaged zip codes to be scores 5 through 9 ($N = 61$) based on socioeconomic factors (37).

Number of SHIELD test centers

The effective number of SHIELD test centers defined as the proportion of a test center's service to a given area. 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 1000 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 proportion of a zip code served by a test center	1.59	2.676
State ADI	Independent	Categorical	The ADI score for each zip code	Median = 4	Q1:Q4 = 3:9

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.

1 **Statistical Analyses**

2 Three linear mixed-effects Poisson regression (LMER) models were employed to investigate the

3 association between the effective number of SHIELD test centers and the COVID-19 ICU admission rate.

4 We focused on data from March 2021 to June 2021 for the Alpha wave, August 2021 to November 2021

5 for the Delta wave (40), and December 2021 to March 2022 for the Omicron wave (2). The Beta and

6 Gamma COVID-19 waves are not considered because of the small number of patients involved (41). The

7 models include fixed effects such as the effective number of SHIELD centers per zip code per month and

8 the ADI category. We incorporate a zip code-level random intercept for the monthly COVID-19 ICU

9 admission rate clustering. The details of the models are as follows:

10 - Model 1 evaluates the direct effect of the effective number of SHIELD centers on ICU admission

11   rates without considering any additional covariates or interaction terms.

12 - Model 2 introduces the ADI (High Disadvantaged) variable to examine how socioeconomic

13   deprivation influences ICU outcomes, allowing for a deeper understanding of disparities across zip

14   codes.

15 - Model 3 builds on the previous models by incorporating an interaction term between the effective

16   number of SHIELD centers and ADI (High Disadvantaged). This interaction term helps identify

17   whether the presence of SHIELD centers has a differential impact in highly disadvantaged areas

18   compared to low disadvantaged ones.

19 Additionally, we conducted robust checks using lag analysis to assess the impact of SHIELD testing on the

20 COVID-19 ICU admission rate across different waves. We examined the effects with two-month lags to

21 determine whether the timing of testing influenced subsequent COVID-19 ICU admissions (42). 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. Additionally, assistance from ChatGPT, a large language model developed by OpenAI, is used for language editing and clarity improvements. The authors have reviewed and approved all final content to ensure accuracy and integrity.

Results

The 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. 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. Figure 3 illustrates the relationship between the effective number of SHIELD test centers and COVID-19 ICU admission rates, both averaged over time, across various zip codes categorized by their ADI levels.
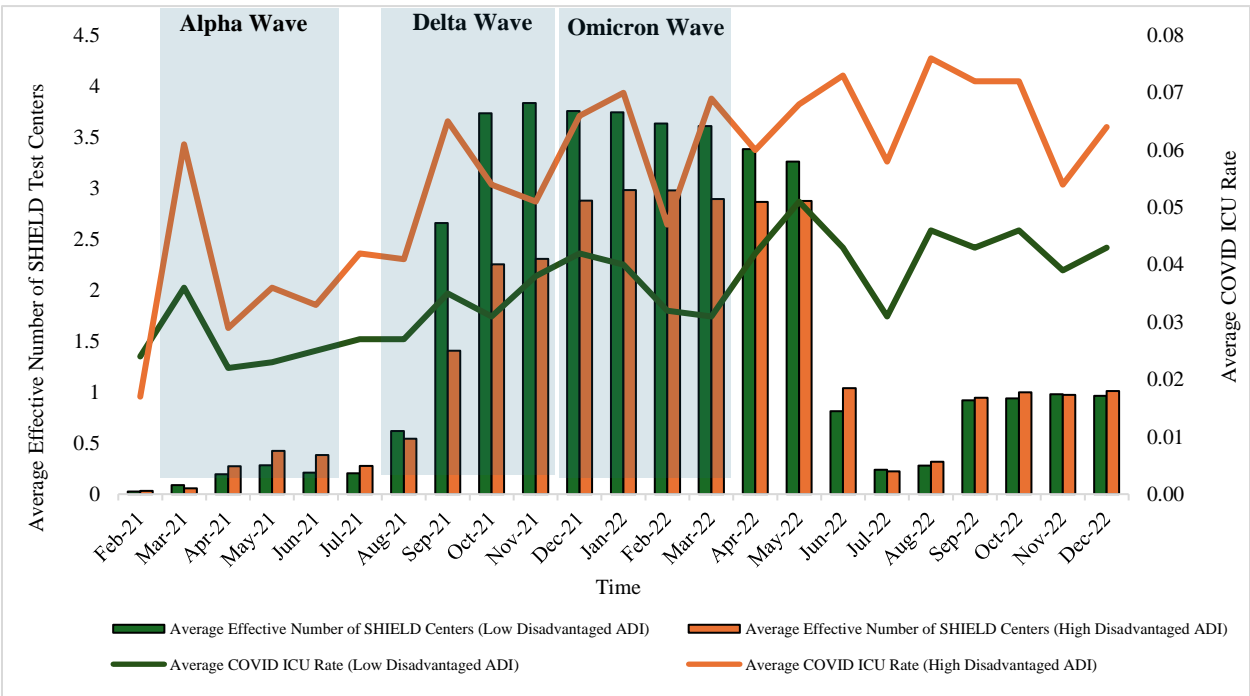

Figure 3: Trends in COVID-19 ICU admission rates and effective number of SHIELD test centers across zip codes over time

Linear Mixed-Effect Regression Model

9

1 Table 2 summarizes regression models examining the relationship between the effective number of

2 SHIELD test centers and COVID-19 ICU admission rates during the Alpha, Delta, and Omicron waves.

3 While none of the models indicate a significant impact of SHIELD test centers in disadvantaged areas

4 during the Alpha wave, Model 2 during the Delta wave shows that high-disadvantaged zip codes have a

5 1.6% increase in the IRR compared to those with low disadvantage. These findings indicate that higher

6 ADI areas experienced elevated COVID-19 ICU admission rates, highlighting socioeconomic disparities

7 in the burden of severe COVID-19 cases. During the Omicron wave, Model 3 shows a statistically

8 significant effect of the effective number of SHIELD centers on COVID-19 ICU admission rates, with a

9 0.6% decrease in the incidence rate ratio (IRR) observed in zip codes with higher ADI.

10

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

Independent Variable	Dependent Variable: COVID-19 ICU Admission Rate								
	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	0.994 (0.005)	1.000 (0.001)	0.997 (0.002)						
ADI (High vs Low Disadvantaged)				1.008 (0.008)	1.016* (0.009)	1.021 (0.012)			
Effective Number of SHIELD Centers by ADI (Low Disadvantaged)							0.991 (0.009)	1.000 (0.001)	1.000 (0.002)
Effective Number of SHIELD Centers by ADI (High Disadvantaged)							0.995 (0.007)	0.998 (0.002)	0.994* (0.002)
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

NOTE: The LMER model included fixed effects such as the effective number of SHIELD centers per zip code per month and the ADI category. A random effect for zip code was also included. The unit of observation is the number of zip codes that have patients in LUMC ICU. All numbers in the table represent exponentiated coefficients (IRR) with 95% Confidence Intervals, and Standard Errors are shown in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$

11

12 **Lag Analysis**

13 Table 3 displays a regression analysis investigating the influence of SHIELD test centers and ADI on

14 COVID-19 ICU admission rates with a two-month delay. While none of the models indicate a significant

15 impact of SHIELD test centers in disadvantaged areas during the Alpha wave, in the Delta wave, Model 1

presents a negative and statistically significant estimate which indicates a 0.2% decrease in IRR for effective number of SHIELD test centers per unit increase. This indicates a considerable reduction in the COVID-19 ICU admission rate two months after an increase in the effective number of SHIELD test centers. Also, Model 2 during the Delta wave shows that high-disadvantaged zip codes have a 1.6% increase in the IRR compared to low-disadvantaged areas. These findings indicate that higher ADI areas experienced elevated COVID-19 ICU admission rates, highlighting socioeconomic disparities in the burden of severe COVID-19 cases. During the Omicron wave, Model 3 demonstrates a statistically significant association between the effective number of SHIELD centers and COVID-19 ICU admission rates, with a 0.7% decrease in IRR observed in zip codes with higher ADI. For all models in the analysis, multicollinearity is assessed using the Variance Inflation Factor (VIF), with all VIF values remaining below 4. This indicates that multicollinearity is not a concern in the models, ensuring reliable coefficient estimates.

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

Independent Variable	Dependent Variable: COVID-19 ICU Admission Rate								
	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	0.998 (0.003)	0.998* (0.001)	0.997 (0.001)						
ADI (High vs Low Disadvantaged)				1.008 (0.008)	1.016* (0.009)	1.020 (0.012)			
Effective Number of SHIELD Centers by ADI (Low Disadvantaged)							1.000 (0.003)	0.999 (0.002)	1.000 (0.002)
Effective Number of SHIELD Centers by ADI (High Disadvantaged)							0.992 (0.005)	0.996 (0.002)	0.993** (0.002)
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

NOTE: The LMER model included fixed effects such as the effective number of SHIELD centers per zip code per month and the ADI category. A random effect for zip code was also included. The unit of observation is the number of zip codes that have patients in LUMC ICU. All numbers in the table represent exponentiated coefficients (IRR) with 95% Confidence Intervals, and Standard Errors are shown in parentheses.
***p<0.01, **p<0.05, *p<0.1

Finally, 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

1   these two metrics (see Appendix 4). While some variation exists, this small RMSE suggests that, in general,

2   the centers were effective in serving their communities.

3   **Discussion**

4   Our study evaluated how SHIELD testing influences the severity of outcomes, particularly ICU admissions,

5   with a focus on disadvantaged communities. This study demonstrates that the impact of the SHIELD testing

6   program was not solely dependent on the number of testing centers but on their strategic deployment in

7   reducing COVID-19 ICU admissions, particularly in socioeconomically disadvantaged areas. Our findings

8   suggest that higher disadvantaged areas consistently experienced higher ICU admission rates despite an

9   increase in test centers, emphasizing the importance of targeted resource allocation.

10   Other studies have leveraged SHIELD data to assess its role in managing COVID-19, focusing on

11   optimizing resource allocation, reducing transmission rates, and improving testing outcomes in educational

12   settings (43–45).

13   To provide a more accurate understanding of the program's impact, this study highlights the importance of

14   the effective number of SHIELD test centers, which is defined as the proportion of a test center's service

15   to a given area. While test centers are located in facilities such as schools within specific zip codes, many

16   students attend schools outside their residential areas. Since students represent their home communities,

17   considering the effective number of centers better reflects the broader reach of testing across adjacent

18   regions.

19   Our analysis indicates that as the overall number of SHIELD test centers increased during major pandemic

20   waves, the proportion of centers effectively serving their respective zip codes was associated with reduced

21   COVID-19 ICU admission rates. According to Figure 3, averaging overtime minimizes short-term

22   fluctuations, enabling more reliable comparisons across zip codes and deprivation levels. The data shows

23   that during the peaks of the pandemic, particularly during the Delta and Omicron waves, the number of

24   SHIELD test centers increased significantly in both highly disadvantaged and low-disadvantaged areas.

25   However, low-disadvantaged areas consistently maintained a higher number of effective test centers

throughout the period. One possible explanation must be related to the unbalanced number of zip codes served by LUMC. Despite the rise in test centers, COVID-19 ICU admission rates remained notably higher in high disadvantaged zip codes, especially during these waves. This suggests that, even with increased access to testing, socioeconomically disadvantaged areas faced a disproportionately heavier burden of severe COVID-19 cases, underscoring the persistent health disparities in these communities during the pandemic.

The LMER models' results demonstrate the evolving relationships between SHIELD test centers and ICU admission throughout the pandemic. During the Alpha wave, the presence of test centers showed limited association with ICU admissions, likely to reflect early-stage testing efforts that were not yet fully optimized or widespread. By the Delta and Omicron waves, the data indicate stronger associations between the effective use of test centers and reduced ICU admissions, particularly in disadvantaged areas (higher ADI scores). The positive association observed during the Delta wave 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 during the Omicron wave, correlated with an increase in the effective number of SHIELD test centers, suggests that improved access and utilization of these centers may have contributed to mitigating severe outcomes. Our data showed that the average COVID-19 ICU admission rate was 0.063 per 1,000 population during the Omicron wave. Analyses revealed that adding one SHIELD test center in high-disadvantaged zip codes could reduce the ICU admission rate by 0.38 per 1,000 population, highlighting the effectiveness of targeted interventions in addressing disparities in these communities. 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 lag analysis further illustrates the evolving relationship between SHIELD test centers and COVID-19 ICU admissions, especially when considering a two-month delay. During the Alpha wave, the presence of SHIELD test centers showed limited association with ICU admissions in disadvantaged areas, likely

reflecting early-stage testing infrastructure that was not yet 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 association suggests that expanded testing efforts may have played a role in alleviating severe outcomes over time. Specifically, a higher number of effective SHIELD test centers corresponded with a reduced burden on healthcare systems during the Delta wave, emphasizing the importance of sustained and targeted testing initiatives. Despite these improvements, disadvantaged zip codes continued to face disproportionately higher ICU admission rates, as reflected in the positive association found during Delta wave. 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. Our data showed that during the Delta wave, adding one SHIELD test center was estimated to reduce the COVID-19 ICU admission rate by 0.1 per 1,000 population. Also, adding one SHIELD test center was estimated to lower the COVID-19 ICU admission rate in highly disadvantaged zip codes by 0.45 per 1,000 population. These findings demonstrate that by strategically increasing testing in disadvantaged communities, significant reductions in severe outcomes can be achieved, even with a delayed effect.

The main limitation of this study is that it relies on ICU data from a single hospital, which may affect the generalizability of the findings. However, the hospital serves a racially, economically, and linguistically diverse population, reflecting the demographics of its surrounding area, Cook County (Appendix 5). This includes a significant proportion of individuals from underrepresented groups and economically disadvantaged backgrounds, providing valuable insights into the impact of SHIELD test centers on diverse communities. Despite this, future studies should incorporate data from multiple hospitals to capture a broader and more representative perspective.

The SHIELD Illinois program was conducted solely within Illinois, primarily near urban areas, without consideration of data from other states or more rural regions. This restricts the ability to evaluate SHIELD's

effectiveness in different geographic contexts. Future research should assess similar programs across multiple states to provide more generalizable findings. Furthermore, key factors such as comorbidities, vaccination status, and early treatment interventions were not accounted for in this study, which may influence ICU outcomes. Including these variables in future research would offer a more comprehensive understanding. Lastly, the voluntary nature of SHIELD participation may have introduced selection bias, as wealthier districts were more likely to adopt the program early. Addressing these limitations will provide a clearer assessment of SHIELD's overall impact and help guide equitable resource allocation in future pandemic responses.

Conclusion

This study demonstrates that the impact of the SHIELD testing program was not solely dependent on the number of testing centers but on their effectiveness in reducing COVID-19 ICU admissions, particularly in socioeconomically disadvantaged areas. Our findings suggest that higher disadvantaged areas consistently experienced higher ICU admission rates despite an increase in test centers, emphasizing the importance of targeted resource allocation. The strategic placement and utilization of SHIELD centers in these communities were crucial for mitigating severe health outcomes. Future public health strategies should prioritize not only the expansion of testing facilities but also their optimal placement and operation in vulnerable areas to maximize their effectiveness in reducing severe outcomes during pandemics. Further research will focus on refining the placement of testing centers to improve both coverage and equity in disadvantaged regions.

Abbreviations

ICU: Intensive Care Unit

ADI: Area Deprivation Index

EHR: Electronic Health Record

IRB: Institutional Review Board

1 *LUMC:* Loyola University Medical Center

2 *LMER:* Linear Mixed-Effects Regression

3 *IRR: Incident Rate Ratio*

4 *SE:* Standard Error

5 *VIF:* Variance Inflation Factor

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

Table A.1 shows a list of ICD-10 codes used to classify COVID-19-related conditions and diagnoses. Each code represents a specific health condition directly associated with COVID-19, ranging from exposure to the virus to post-COVID complications.

Table A.1: ICD-10 codes related to COVID-19

COVID-19-related ICD-10 code	Description
Z11.52	Contact with and (suspected) exposure to COVID-19
M35.81	Multisystem Inflammatory Syndrome (MIS)
J12.82	Pneumonia due to Coronavirus disease 2019
U07.1	COVID-19
U09.9	Post-COVID-19 condition, unspecified
B97.29	Other Coronavirus as the cause of disease classified elsewhere
J20.8	Acute bronchitis confirmed as due to COVID-19
J22	Lower or acute respiratory infection due to COVID-19
J98.8	Respiratory infection due to COVID-19

1

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

3 In this model, i represents the index for each SHIELD test center, j corresponds to each zip code, and t

4 denotes time. The variable S_{ijt} is the number of COVID-19 samples collected from zip code j by test center

5 i in time t, while T_{jt} represents the total number of samples collected from zip code j by all test centers in

6 in time t. The proportion of samples collected by test center iii from zip code j in time t, denoted as

7 $P_{ijt} = \frac{S_{ijt}}{T_{jt}}$. The effective number of SHIELD test centers serving zip code j in time t, denoted as

8 $E_{jt} = \sum_i P_{ijt}$, is then determined by summing these proportions across all test centers, capturing the

9 distribution of service provided by the centers in relation to the zip code. This approach quantifies the

10 contribution of multiple centers in testing coverage for each zip code.

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

12 The total number of ICU admissions in zip code j during time t is represented by ICU_j^t, and the population

13 of zip code j is denoted as Pop_j. The COVID ICU admission rate for zip code j during time t, denoted as

14 $ICU\_Rate_j^t$, is calculated as the ratio of the total ICU admissions to the population of the zip code. This rate

15 captures the proportion of ICU admissions related to COVID-19 in a given zip code relative to its

16 population, providing a standardized measure of the ICU burden on the local healthcare system. The

17 formula is:

18
$$ICU\_Rate_j^t = \left(\frac{ICU_j^t}{Pop_j}\right) \times 1000$$

19 This formula calculates the number of ICU admissions per 1,000 people for a given zip code j in time t

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

1   Figure A.1 shows the trends of the number of SHIELD test center versus effective number of SHIELD test
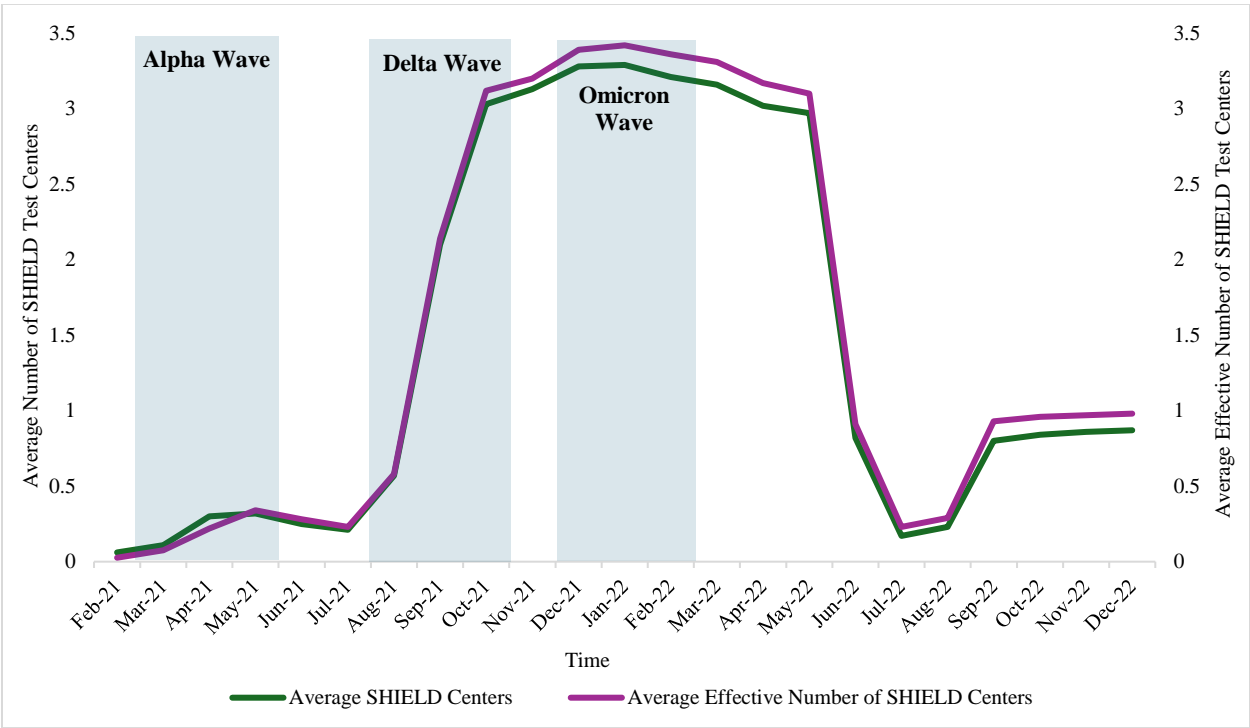
2   centers for all zip codes over time.

3
4   **Figure A.1:** Trends of SHIELD test centers and effective number of SHIELD centers over time for all zip codes
5

6   **Appendix 5: Comparison of LUMC ICU Cohort with Cook County and National Averages** (46).

7   Table A.2 compares demographic characteristics of the LUMC ICU cohort with Cook County and national

8   averages, highlighting differences in race, gender, language, and socioeconomic factors.

9   **Table A.2:** Demographic Comparison of LUMC ICU, Cook County, and National Averages

Characteristic	LUMC ICU Cohort	Cook County	National Average
Black/African American Patients (%)	19	23.8	13.4
Female Patients (%)	43.3	51.4	50.8
Non-English Speakers (%)	35	35	21.5
Hispanic Population (%)	-	26.1	18.5
Poverty Rate (%)	-	13	11.4

10   **Declarations**

Ethics approval and consent to participate

Not Applicable

Consent for publication

The authors affirm that all participants involved in this study, or their legal guardians, have given their consent for the publication of any potentially identifying information contained within the manuscript. No personal or sensitive data (such as images, personal health information, or identifiable demographics) will be included that could compromise the privacy or anonymity of the participants. Where applicable, participants provided informed consent in accordance with ethical guidelines and institutional policies. Furthermore, this manuscript does not contain any individual-level data or other content requiring consent for publication.

Availability of data and materials

Not Applicable

Competing interests

The authors declare no competing interests.

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7   **Authors' contribution**

8   A.K. was responsible for design of the study, data analysis, and manuscript writing. A.W. contributed

9   valuable insights into the results and analyses and assisted in reviewing and editing the manuscript. F.I. and

10   M.S. played key roles in data preprocessing and graphic design. W.P. M.S. S.A. S.T. and N.S. reviewed the

11   manuscript, provided critical feedback, and contributed to funding acquisition (PI: S.T.) Additionally, S.A.

12   and S.T. conceptualized the study and contributed to manuscript editing and analysis insights.