Evaluation of Rhode Island's Early Geographic COVID-19 Vaccine Prioritization Policy

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Objectives. To determine whether geographic prioritization of limited COVID-19 vaccine supply was effective for reducing geographic disparities in case rates.

Methods. Rhode Island allocated a portion of the initial COVID-19 vaccine supply to residents of Central Falls, a community already affected by structural policies and inadequate systems that perpetuate health inequities and experiencing disproportionately high COVID-19 morbidity and mortality. The policy was implemented with a culturally and linguistically appropriate community engagement plan and was intended to reduce observed disparities. Using a Bayesian causal analysis with population surveillance data, we evaluated the impact of this prioritization policy on recorded cases over the subsequent 16 weeks.

Results. Early geographic prioritization of Central Falls accelerated vaccine uptake, averting an estimated 520 cases (95% confidence interval = 22, 1418) over 16 weeks and reducing cases by approximately 34% during this period (520 averted vs 1519 expected without early prioritization).

Conclusions. Early geographic prioritization increased vaccine uptake and reduced cases in Central Falls, thereby reducing geographic disparities.

Public Health Implications. Public health institutions should consider geographic prioritization of limited vaccine supply to reduce geographic disparities in case rates. (*Am J Public Health*. 2024;114(S7): S580–S589. https://doi.org/10.2105/AJPH.2024.307741)

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Substantial disparities in COVID-19 morbidity and mortality have been apparent since the onset of the pandemic in the United States, particularly by race/ethnicity, socioeconomic status, and geography.[1–4] Black or African American and Hispanic or Latino people have experienced higher rates of COVID-19 diagnosis and mortality than White people,[5] as have people of lower socioeconomic status.[6] Geographic disparities in COVID-19 case rates often result from structural inequities (e.g., isolation is more difficult in crowded households)[7] and financial pressure or essential worker status, increasing hesitancy to get tested or isolate[7] and compounding other disproportionate social and economic impacts of the pandemic. These COVID-19 disparities are consistent with those observed for other health conditions in the United States,[8] reflecting the strong influence of social and structural factors. Key social determinants of health include economic stability, access to high-quality education and health care, a safe neighborhood and built environment, and community context.[9] These social determinants have contributed to COVID-19 disparities directly and through their association with preexisting chronic health conditions that increase risk of severe COVID-19 if infected.[2]

Early in the pandemic, some state and local agencies implemented programs intended to reduce health disparities, including targeted quarantine and isolation supports, cash assistance, and care navigation.[10] As the COVID-19 vaccine became available, new opportunities to improve health equity emerged,[11] particularly given the initial limited supply and high demand. The most common approaches to determining early vaccine eligibility were based on age, occupation (e.g., essential workers), and chronic conditions. Although some jurisdictions aimed to incorporate other criteria into their early vaccine prioritization policies, such as race/ethnicity and geography, these policies were often controversial and ultimately abandoned.[12–17] However, simulation studies suggest that early COVID-19 vaccination strategies that prioritized people of all ages in geographic areas at high risk for adverse health outcomes may have prevented more deaths than purely age-based strategies.[18]

The Rhode Island Department of Health (RIDOH) implemented an early COVID-19 geographic vaccine prioritization policy to provide rapid access for residents of communities[19–21] with high COVID-19 cases, morbidity, and mortality, high population density, and preexisting structural policies and inadequate systems that perpetuate health inequities. The policy, which was implemented with a robust culturally and linguistically appropriate community engagement plan, was intended to decrease disparities by reducing COVID-19 case rates in prioritized communities toward levels observed in other communities. To increase vaccine uptake, the engagement plan included the dispatch of canvassers who spoke the same languages as community residents to provide information on the vaccine and assist with registration for vaccine appointments, as well as partner with community-based organizations on education and outreach. Adult residents of Central Falls became eligible for vaccination nearly 4 months before all adults statewide,[19] and adults in other disproportionately affected communities became eligible between 1 and 4 weeks early.[20,21] Consistent with national data, Rhode Island had experienced persistent disparities in COVID-19 case rates, morbidity, and mortality, with people of color and those residing in urban core communities most affected.[22–25]

Evaluation of this policy is critical for understanding the extent to which it reduced observed disparities. Additionally, understanding the effectiveness of this policy can inform future resource allocation strategies in the context of limited resources. Thus, we aimed to evaluate the impact of Rhode Island's early COVID-19 geographic vaccine prioritization policy on cases in Central Falls and to consider the potential impact of alternative geographic prioritization scenarios.

METHODS

In this section, we describe the identification of communities disproportionately affected by the COVID-19 pandemic, the specific eligibility strategies within Rhode Island's geographic vaccine prioritization policy, and the statistical methods of our policy evaluation.

Identification of Communities

Our evaluation focused on Rhode Island residents, accounted for by community of residence, with few exclusions. Hereafter, we use "community" to refer to any of the 57 monitoring regions considered in this analysis, which were generally defined at the zip code tabulation area (ZCTA) level. However, for the 8 municipalities containing at least 1 ZCTA with population less than 1000, ZCTAs were summed to the municipality level (Appendix A.2, available as a supplement to the online version of this article at https://www.ajph.org).

Some aspects of this evaluation considered communities using a 3-tier community risk classification created by RIDOH to help guide COVID-19 surveillance and response efforts. RIDOH assigned each ZCTA to a tier based on community characteristics such as population density, social determinants of health, and COVID-19 burden to date. Generally, tier 1 was considered at highest risk, tier 2 at moderate risk, and tier 3 at lowest risk for SARS-CoV-2 infection and associated COVID-19 morbidity and mortality. RIDOH also used these tier designations to determine geographic prioritization strategies for COVID-19 vaccination. Because of vaccine supply limitations and the community characteristics listed in Methods, 1 tier 1 community, Central Falls, was identified for earliest prioritization, with prioritization of other tier 1 communities following as supply became available.

Data and Measures

We used RIDOH surveillance data to define weekly counts of administered COVID-19 vaccine doses and recorded cases disaggregated by ZCTA. To obtain community-level sociodemographic characteristics, we downloaded all distinct variables used in the calculation of the US Centers for Disease Control and Prevention's (CDC's) Social Vulnerability Index[26] at the ZCTA level from the US Census Bureau,[27] as well as median household income[27] and population density, summing ZCTA-level estimates by community where applicable.

Geographic vaccine eligibility strategies. Using RIDOH's timeline of vaccine eligibility, shown in Appendix A.1 (available as a supplement to the online version of this article at https://www.ajph.org), we identified 4 distinct strategies within the policy, which were implemented using RIDOH's ZCTA-based tier designations.

The differentiating factor was the timing of communitywide eligibility for all adult residents (aged ≥ 16 years). Specifically, the timing of adult eligibility under the 4 strategies was as follows:

1. December 28, 2020: Central Falls (1 specific tier 1 community, ZCTA 02863);
2. March 22, 2021: remaining tier 1 communities;
3. April 12, 2021: tier 2 communities; and
4. April 19, 2021: tier 3 communities.

Under limited vaccine supply, adult residents of Central Falls became eligible for vaccination nearly 3 months earlier than residents of other tier 1 communities (and nearly 4 months earlier than residents statewide) because of periods with exceptionally high prevaccine case, hospitalization, and mortality rates—even relative to other tier 1 communities—and community characteristics. Such community characteristics included disproportionate disease burden among young, Hispanic/Latino, and Black residents; a high percentage minority and undocumented residents; high population density; preexisting structural policies and inadequate systems that perpetuate health inequities, such as a lack of health infrastructure; and small population size. Thus, we refer to Central Falls as a tier 1* community, and it is the main focus of our policy evaluation. Other tier 1 and tier 2 communities became eligible 1 to 4 weeks earlier than residents statewide.

During the policy implementation period, residents throughout the state also became eligible for vaccination based on age, occupation, chronic conditions, and residence in a congregate care setting. For instance, at the time when all adult residents of Central Falls (tier 1*) became eligible for vaccination, only health care workers and those living or working in congregate care settings were already eligible for vaccination. However, by the time all adult residents of tier 1 and 2 communities became eligible, older age groups and those with chronic conditions statewide had already gained eligibility gradually throughout February and March 2021.

We used the 4 tier-based eligibility strategies to determine the percentage of each community that was eligible for vaccination at any given time, using this percentage as a time-varying continuous intervention that was fully determined by the strategy assignment and the age distribution of the community.

Outcome. Our primary outcome was recorded COVID-19 cases averted at the community level, under different geographic vaccine eligibility strategies. During the study period, all positive SARS-CoV-2 tests were reported to RIDOH. We also model an intermediary outcome, COVID-19 vaccine uptake, measured as the percentage of the community that had received at least 1 vaccine dose.

Sociodemographic covariates. As described briefly in the introduction, RIDOH allocated a portion of the initial supply of COVID-19 vaccines to residents of communities with characteristics identified through sustained monitoring efforts: disproportionately high COVID-19 cases, morbidity, and mortality, including elevated rates of infection and hospitalization among young people; a high percentage of minority and undocumented residents, increasing the importance of culturally relevant outreach; high population density; and preexisting structural policies and inadequate systems that perpetuate health inequities.[19–21]

Our model relies on a version of the treatment ignorability (no unmeasured confounders) assumption to infer the effect of eligibility assignment: the assignment of eligibility strategy depends only on measured, preassignment covariates and—conditional on those covariates—it is independent of the potential level of vaccine uptake and number of cases that might result from early eligibility assignment. In practical terms, we assumed that assignment of eligibility was dependent on community-level covariates that were known in advance. Thus, it was crucial to understand the motivation for RIDOH's eligibility decision and adjust accordingly for relevant potential confounders.

We adjusted for measured characteristics to minimize the impact of unmeasured confounding associated with eligibility strategy assignment and recorded COVID-19 cases,[28] including all variables used in the calculation of the CDC's Social Vulnerability Index,[26] recorded COVID-19 cases in the prevaccine period, median household income, and population density. These characteristics are summarized in Table 1.

Statistical Methods

We used a 2-part model to characterize the overall effect of eligibility strategy on longitudinal trends in case counts. Specifically, we assumed that the mechanism through which eligibility strategy affects case counts is by increasing vaccine uptake and that vaccine uptake is driven both by the percentage of the population eligible for vaccination and community-level covariates (for more detail, see Appendix B, available as a supplement to the online version of this article at https://www.ajph.org). We used the following modeling process:

1. Model observed vaccine uptake at the community level as a function

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TABLE 1— Summary of Average Sociodemographic Characteristics by COVID-19 Risk Tier Designation: Rhode Island, March 1, 2020–September 18, 2021

	Tier 1*,[a] (n = 1)	Tier 1 (n = 6)	Tier 2 (n = 9)	Tier 3 (n = 41)
SVI variables, %				
Below 150% of poverty level	48.8	32.1	18.2	11.0
Unemployed	4.6	4.7	3.6	3.4
Housing cost–burdened units	48.9	40.4	32.3	23.6
No high school diploma	35.9	18.5	11.8	6.8
Uninsured	14.7	7.1	4.5	2.6
Aged ≥ 65 y	7.7	12.3	16.4	20.2
Aged ≤ 17 y	29.1	23.9	18.0	18.1
Disabled	17.6	14.2	14.0	12.3
Single-parent households	11.3	13.3	6.8	4.4
Speak English less than well	17.0	11.8	3.0	1.0
Minorities	79.1	66.6	29.3	10.5
Housing with ≥ 10 units	12.2	14.8	14.3	8.4
Mobile homes	0.0	0.2	0.2	1.5
Crowded housing (> 1 occupant/room)	8.8	4.0	2.0	0.8
Households with no vehicle	22.3	15.8	9.3	5.3
Group quarters	3.2	3.0	3.8	2.7
Additional variables				
Population density (per sq mi)	16 194	9 888	5 226	1 166
Median household income, $	34 689	46 641	64 865	88 923
Recorded cases per 100 000 (March–November 2020)	2 295	3 016	1 256	376
% of population with at least 1 dose as of September 18, 2021	69.9	61.9	65.1	68.1
% of population with at least 2 doses as of September 18, 2021	60.1	55.1	60.2	63.9

Note. The table includes all variables used in the calculation of the Social Vulnerability Index (SVI) and the additional sociodemographic variables used in the models. SVI variables are the percentages of the population with that characteristic. Tiers refer to the 3-tier community risk classification system developed by the Rhode Island Department of Health to help guide COVID-19 surveillance and response efforts. Tier 1 included communities at highest risk for COVID-19 and tier 3 included communities at lowest risk (see Methods).

[a]Under limited vaccine supply, adult residents of Central Falls became eligible for vaccination nearly 3 months earlier than residents of other tier 1 communities (and nearly 4 months earlier than residents statewide) because of periods with exceptionally high prevaccine case, hospitalization, and mortality rates.

of eligibility, sociodemographic variables, and time.

2. Model recorded case counts at the community level as a function of vaccine uptake, sociodemographic variables, and time.
3. Using the model in step 1, generate predicted vaccine uptake as a function of time for each community under each eligibility strategy.
4. Using the model in step 2, generate predicted number of recorded cases as a function of time, using vaccine uptake predictions generated in step 3. This yields predicted potential outcomes of recorded cases under each of the eligibility strategies for each community.
5. Compute causal effects in terms of the difference in predicted cases under different eligibility strategies.

We used Bayesian machine learning models for the predictive models in steps 1 and 2 to capture potential nonlinearities and interactions without having to specify the precise functional form of the models. Steps 3 through 5 were carried out using posterior predictive sampling from the models, which can be viewed as simulations from fitted models under each strategy.

Specifically, we used soft Bayesian Additive Regression Trees (SoftBart)[29,30] to learn observed data models (steps 1 and 2 above). Briefly, SoftBart is a Bayesian nonparametric method for modeling an unknown function as an ensemble of decision trees, aggregating numerous weakly informative decision trees, each explaining a small portion of the unknown function, into a strong learner, while regularizing the impact of each tree.[29] Unlike general BART models, SoftBart assigns probabilities to each split rather than hard cutoffs, resulting in smooth predictions with reduced error compared to general BART implementations.[29,31] This modeling strategy allowed us to examine every possible interaction among numerous potentially correlated predictors, while prioritizing lower-order interactions, and to estimate causal effects by drawing posterior predictions at the community level. We used default parameter settings. Detailed modeling information is available in online Appendix B.

To evaluate the impact of the eligibility strategy implemented in Central Falls, we compared the predicted number of recorded cases under the tier 1* strategy implemented to that predicted under the tier 3 strategy (i.e., assuming no geographic prioritization) during the period of early prioritization. Similarly, we estimated the potential impact of alternative geographic prioritization scenarios for tier 1 and tier 2 communities, given sufficient vaccine supply, by comparing the predicted number of cases under the tier 1* strategy (i.e., if they had received earliest prioritization) versus the strategy actually implemented for each community.

We implemented all analyses using R version 4.0.2, fitting models using the SoftBart package.[30]

RESULTS

Our analysis included 57 communities in Rhode Island, ranging in population from 2194 to 47 174. Of the 1 046 263 people residing in those 57 communities, 19 437 (1.9%) resided in the tier 1* community, 212 431 (20.3%) in tier 1 communities, 249 017 (23.8%) in tier 2 communities, and 565 378 (54.0%) in tier 3 communities. From March to November of 2020, there were 20 333 COVID-19 cases recorded in tier 1* and tier 1 communities combined, more than half of the state's 40 179 total recorded cases during this period, despite only 22.2% of the state's population residing in these communities. Case rates were consistently higher in tier 1* and tier 1 communities than in tier 2 and tier 3 communities during this prevaccine period (Figure 1).

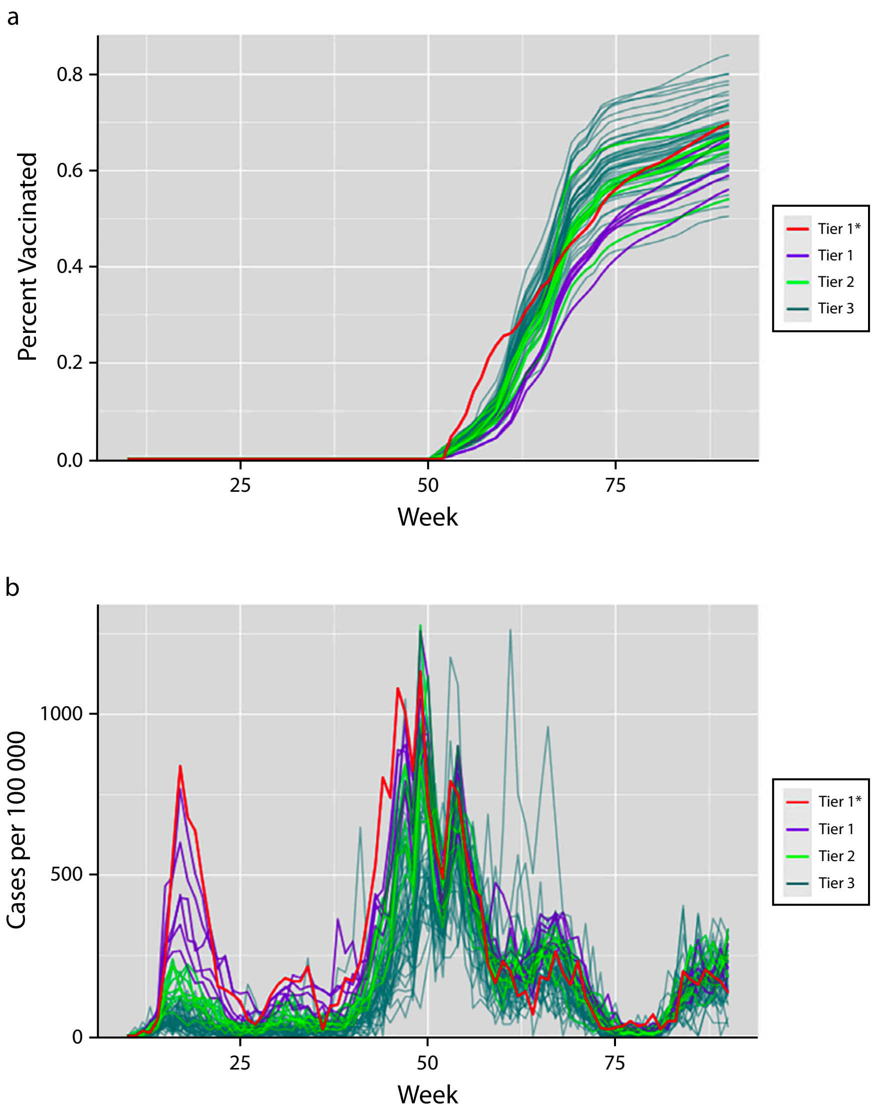

FIGURE 1— Community Statistics for (a) Observed COVID-19 Vaccine Uptake and (b) Recorded Cases of COVID-19 per 100 000 Population: Rhode Island, March 1, 2020–September 18, 2021

Note. The figure shows the observed data for the 57 communities that we used to fit our model in each stage of the analysis. The horizontal axes spans March 1, 2020 (week 10), to September 18, 2021 (week 90). Tiers refer to the 3-tier community risk classification system developed by the Rhode Island Department of Health to help guide COVID-19 surveillance and response efforts. Tier 1 included communities at highest risk for COVID-19 and tier 3 included communities at lowest risk (see Methods). In each panel, lines representing community-level metrics are colored by tier assignment. Vaccine uptake is measured as the proportion of the population with at least 1 dose of an approved vaccine, while cases are measured as recorded case counts per 100 000 population.

[a]Under limited vaccine supply, adult residents of Central Falls became eligible for vaccination nearly 3 months earlier than residents of other tier 1 communities (and nearly 4 months earlier than residents statewide) because of periods with exceptionally high prevaccine case, hospitalization, and mortality rates.

Disparities in social determinants of health were also apparent across the tiers (Table 1). For example, the percentage of the population living below 150% of the federal poverty level ranged from 48.8% in the tier 1* community to 32.1% in tier 1, 18.2% in tier 2, and 11.0% in tier 3 communities. Similarly, the percentage of the population with no high school diploma ranged from 35.9% in the tier 1* community to 6.8% in tier 3 communities, whereas living in crowded housing ranged from 8.8% in the tier 1* community to 0.8% in tier 3 communities.

Impact of Rhode Island's Policy

The observed vaccine uptake (Figure 1a) and recorded case rate (Figure 1) differed substantially by community over time. Of note, the initial and end-of-study (September 18, 2021) observed vaccine uptake in Central Falls (tier 1*) was higher than in any tier 1 community.

Our models for vaccine uptake and recorded cases by community exhibited good fit to the observed data over time. Example curves of model fit for a community in each tier are available in Figure A1 (available as a supplement to the online version of this article at https://www.ajph.org).

As previously noted, our evaluation focused on the policy impact in Central Falls because of the community characteristics and the wider timeline distinction between the strategy implemented in Central Falls and any other strategy. Compared with a scenario where Central Falls followed the tier 3 strategy (i.e., no geographic prioritization), the tier 1* strategy implemented in Central Falls is estimated to have averted 520 (95% confidence interval [CI] = 22, 1418) recorded cases over 16 weeks, corresponding to 167 (95% CI = 7, 456) cases averted per 100 000 residents per week during this 16-week period. For context, Central Falls has an estimated population of 19 437 and observed 999 cases over this 17-week period. Thus, early prioritization is estimated to have reduced cases by approximately 34% during this period (i.e., 520 averted vs 1519 expected without early prioritization).

Potential Alternative Scenarios

Using modeled vaccine uptake and recorded cases under each strategy by community, we also considered potential alternative prioritization scenarios, given sufficient vaccine supply. Predicted vaccine uptake and recorded case curves under each eligibility strategy for 1 selected community in each tier are available in online Figure A2. In each community, compared with any other eligibility strategy, the tier 1* eligibility strategy resulted in more rapid vaccine uptake and a more rapid decrease in recorded cases. Differences between the other 3 strategies were small.

Compared with the actual strategy used, implementing the tier 1* strategy in tier 1 communities would have rapidly reduced recorded case rates to a more equitable level (Figure 2). We are defining "equitable" here as case rates in the range of what tier 3 communities were experiencing. Overall, implementation of the tier 1* strategy in tier 1 communities would have averted an estimated 3363 (95% CI = 433, 7455) recorded cases over 12 weeks, corresponding to 132 (95% CI = 36, 621) cases averted per 100 000 residents per week during this 12-week period and a 35% reduction in cases during this period (i.e., 3363 averted vs 9620 observed; Table 2).

Similarly, implementation of the tier 1* strategy in tier 2 communities would have rapidly reduced case rates to a more equitable level (Figure 2 and online Figure A3). Overall, implementation of the tier 1* strategy in all tier 2 communities would have averted an estimated 3657 (95% CI = 170, 8131) recorded cases over 15 weeks, corresponding to 98 (95% CI = 5, 218) cases averted per 100 000 residents per week during this 15-week period and a 30% reduction in cases during this period (i.e., 3683 averted vs 12 332 observed).

DISCUSSION

In this evaluation of an early COVID-19 geographic vaccine allocation policy implemented in Rhode Island, we found substantial benefits of early eligibility for residents of a community (Central Falls) with disproportionately high COVID-19 morbidity and mortality, high population density, and preexisting social policies and inadequate systems that perpetuate health inequities. All adults in Central Falls became eligible for vaccination nearly 4 months earlier than all adults statewide. This eligibility strategy for Central Falls accelerated vaccine uptake, thereby resulting in approximately 34% lower recorded cases than would have been expected if the community had not received early eligibility. Our study also suggests that, given sufficient vaccine supply, a similar strategy would have benefited other tier 1 and tier 2 communities. Although our analysis focused on recorded cases, these findings are generally consistent with a simulation study suggesting that geographic vaccine prioritization may prevent more deaths than age-based strategies.[18]

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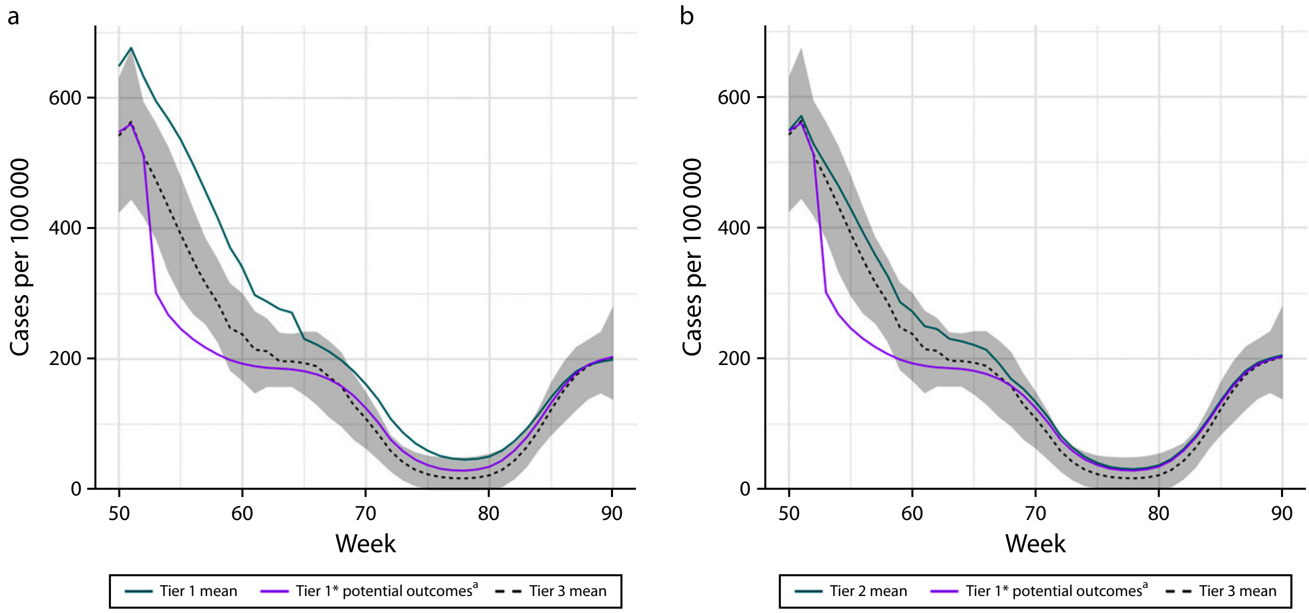

FIGURE 2— Estimated Case Counts Under Differing Strategies for COVID-19 Risk (a) Tier 1 and (b) Tier 2 Communities: Rhode Island, March 1, 2020–September 18, 2021

Note. One realistic alternative to prioritizing Central Falls in December 2020 would have been to prioritize additional or all tier 1 or even tier 2 communities. This figure suggests that the tier 1* strategy would have rapidly reduced case rates to a more equitable level (i.e., in the range of what tier 3 communities were experiencing) in tier 1 or tier 2 communities when considered in aggregate. It also highlights that case rate disparities were less severe in tier 2 communities. The purple line in each panel shows the potential recorded case counts per 100 000 population, if the indicated set of communities had been prioritized as early as Central Falls (tier 1* strategy). The turquoise line shows the fitted recorded case counts per 100 000 population under the tier-specific implemented strategy. The black dashed line shows the posterior mean and the shaded region the 95% density interval for the tier 3 communities in aggregate. Tiers refer to the 3-tier community risk classification system developed by the Rhode Island Department of Health to help guide COVID-19 surveillance and response efforts. Tier 1 included communities at highest risk for COVID-19 and tier 3 included communities at lowest risk (see Methods). Figure A3 (available as a supplement to the online version of this article at https://www.ajph.org) displays the same results for each tier 1 community individually.
[a]Under limited vaccine supply, adult residents of Central Falls became eligible for vaccination nearly 3 months earlier than residents of other tier 1 communities (and nearly 4 months earlier than residents statewide) because of periods with exceptionally high prevaccine case, hospitalization, and mortality rates.

In addition to early geographic prioritization, RIDOH's community engagement efforts were likely an essential component of the vaccination approach. Vaccine effectiveness is dependent not just on eligibility but also on uptake, and uptake requires both accessibility and interest in getting vaccinated.[32] RIDOH implemented the early geographic prioritization policy along with a culturally and linguistically appropriate community engagement plan. Though not directly evaluated in our study, this was likely critical because vaccine access and confidence are decreased by the same structural inequities that predispose communities to adverse health outcomes.[32,33] However, even with this robust community engagement plan, many tier 1 and tier 2 communities had lower vaccine uptake than tier 3 communities, suggesting that additional engagement strategies are needed to improve vaccine access and confidence. Such engagement strategies may include identifying vaccine ambassadors and trusted messengers and supporting them in delivering effective messages; offering home-, school-, and workplace-based vaccination to improve access; and trying to combat misinformation, among others.[32]

Limitations

Our analysis has limitations. First, as with all causal models built from observational data, there may be unmeasured confounding. For example, use of nonpharmaceutical interventions aggregated to the community could be related to increased vaccine uptake and reduced case counts. In this scenario, failing to account for use of nonpharmaceutical interventions could lead to overestimation of policy impact. Second, our counterfactual predictions rely on the accuracy of our models of vaccine uptake and case counts. To maximize flexibility and guard against misspecification, we use Bayesian machine learning models that demonstrate good fit to the observed data but, as with any simulation-based approach, the counterfactual predictions cannot be directly verified. Third, there may be geographic spillover, which is not accounted for in the model (e.g.,

TABLE 2— Average Number of Cases of COVID-19 Averted by the Indicated Strategy Comparison: Rhode Island, March 1, 2020–September 18, 2021

Community	Population	No. of Observed Cases	Realized Strategy	Avg No./ Week	Avg No./ Week/ 100 000	Total No. Averted (95% CI)	Total No. per 100 000 (95% CI)	% Reduction
02860	47 175	2 030	Tier 1	53	113	640 (72, 1 377)	1357 (153, 2919)	31
02904	29 881	1 360	Tier 1	37	123	442 (64, 942)	1480 (216, 3153)	33
02905	26 020	1 019	Tier 1	37	143	447 (53, 943)	1719 (204, 3625)	44
02907	31 277	1 262	Tier 1	47	151	567 (59, 1 315)	1812 (190, 4203)	45
02908	37 792	2 027	Tier 1	49	130	588 (67, 1 391)	1557 (178, 3680)	29
02909	40 286	1 922	Tier 1	57	140	678 (82, 1 571)	1683 (203, 3900)	35
Tier 1 (total)	212 431	9 620	Tier 1	280	132	3 363 (433, 7 455)	1583 (204, 3509)	35
02861	24 764	1 273	Tier 2	28	113	420 (32, 971)	1696 (128, 3922)	33
02893	29 283	1 344	Tier 2	28	97	424 (22, 954)	1448 (76, 3258)	32
02895	41 616	2 262	Tier 2	34	82	511 (40, 1 113)	1227 (96, 2676)	23
02906	28 254	1 131	Tier 2	24	85	362 (−51, 966)	1280 (−182, 3418)	32
02910	21 746	1 129	Tier 2	22	103	336 (5, 780)	1545 (22, 3586)	30
02911	15 627	762	Tier 2	24	153	360 (2, 813)	2301 (10, 5203)	47
02914	21 720	1 052	Tier 2	27	126	410 (31, 913)	1889 (141, 4203)	39
02919	29 312	1 598	Tier 2	26	87	384 (−23, 958)	1309 (−78, 3268)	24
02920	36 695	1 781	Tier 2	30	82	451 (30, 1 048)	1229 (83, 2857)	25
Tier 2 (total)	249 017	12 332	Tier 2	244	98	3 657 (170, 8 131)	1468 (68, 3265)	30

Note. CI = confidence interval. Regarding interpretation of the table: in the first row, for example, if community 02860 had received the tier 1* strategy instead of the realized strategy (tier 1), we estimate that they would have seen 53 fewer cases per week or 113 fewer cases per 100 000 residents per week. Community groupings with "(total)" indicate sums of communities; for instance, tier 1 indicates the sum over all tier 1 communities. The "No. of Observed Cases" column displays the number of cases recorded in that community over the time period between full eligibility in Central Falls and full eligibility in that community. Tiers refer to the 3-tier community risk classification system developed by the Rhode Island Department of Health to help guide COVID-19 surveillance and response efforts. Tier 1 included communities at highest risk for COVID-19 and tier 3 included communities at lowest risk (see Methods). The "Community" column contains the zip code tabulation area. Table cells indicating averted cases are the posterior means of all draws from the model. These results, as with results from other Bayesian models, are averages from a distribution of effect sizes, and were similar to results estimated under different model parameters. In Appendix B (available as a supplement to the online version of this article at https://www.ajph.org), we provide additional information on the modeling process and parameter selection.

increased uptake in 1 community could reduce case counts in neighboring communities). If early availability of vaccine in prioritized communities reduces case counts in neighboring communities, not accounting for spillover could lead to underestimation of early prioritization impact. Finally, our analysis relies on counts of recorded cases, which are less than the numbers of infections. Because our analysis was carried out during a period where all positive test results were reported to RIDOH, it is reasonable to assume that reductions in reported cases correspond to reductions in overall infections, but this cannot be directly verified.

It would have been difficult to apply standard techniques for policy evaluation because primary assumptions are not satisfied,[34,35] so we applied a causal modeling approach (for more details, see online Appendix B). Despite the limitations, our analysis was strengthened by its use of population surveillance data to estimate the impact of the policy, rather than relying on techniques not well-suited for this application.

Public Health Implications

Our analysis suggests that an early geographic COVID-19 vaccine prioritization policy rapidly increased vaccine uptake and reduced recorded cases in Central Falls, thereby reducing geographic disparities. Our findings also suggest that other communities disproportionately affected by the pandemic would have also benefited from this very early prioritization, given sufficient vaccine supply. Reducing rates of COVID-19 cases through early vaccination was critical for improving health equity, as this prevents ongoing transmission and associated morbidity and mortality, and residents are able to maintain daily responsibilities. Public health institutions should consider geographic prioritization of limited vaccine supply within pandemic preparedness and response to improve health equity. Importantly, although our analysis identified benefits of geographic prioritization, we did not aim to determine the optimal vaccine prioritization policy in the context of limited resources. Additional research is needed to estimate the policy's impact on COVID-19 hospitalization and mortality, which could identify additional benefits and inform endpoints for an optimal-policy decision framework. Finally, future use of our model to identify the marginal effect of specific social determinants of health on vaccine uptake at the community level could be useful for informing vaccination campaigns. AJPH

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M. Wilson contributed to the initial COVID-19 vaccination policy development and implementation. T. M. Fortnam, L. C. Chambers, A. Bilinski, R. DeVito, and J. W. Hogan contributed to the evaluation concept and statistical analysis. T. M. Fortnam and L. C. Chambers contributed to initial drafting of the article. All authors contributed to interpretation of the findings and critical revision of the article.

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

HUMAN PARTICIPANT PROTECTION

This evaluation was classified as exempt by the Rhode Island Department of Health institutional review board (application 2021-02).

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A Appendix

A.1 Vaccine Eligibility

Table A.1 shows the relevant events in vaccine approval and eligibility that impacted uptake in the state. The events listed in the ”Geographic Eligibility” column comprise the strategies that we evaluated.

Table A.1: Timeline of vaccine approval and eligibility events affecting vaccine uptake in Rhode Island from December 2020 through September 2021. As federally recommended, the first available vaccines were allocated to healthcare workers and congregate care setting staff in mid-December. At the next stage of distribution, Rhode Island began to allocate some doses geographically, along with continued allocation of doses to vulnerable populations by congregate care setting residence, age, and occupation. (EUA = Emergency Use Authorization)

	Scale of Intervention		
Date	Federal Approval	Statewide Eligibility	Geographic Eligibility
12/11/2020	Pfizer EUA		
12/14/2020		Health care workers and congregate setting staff	
12/18/2020	Moderna EUA		
12/28/2020		Congregate care setting residents	Central Falls residents, age 16+
2/7/2021		Age 75+	
2/22/2021		Ages 65-74	
2/27/2021	Janssen EUA		
3/8/2021		K-12 teachers, staff, and childcare providers	
3/12/2021		Ages 60-64 and 16-64 with underlying conditions	
3/22/2021			Tier 1, age 16+
4/12/2021		Ages 40-49	Tier 2, age 16+
4/19/2021		Ages 16-39	Tier 3, age 16+ (full statewide eligibility)
5/13/2021	EUA for ages 12-15	Ages 12-15	

A.2 Definition of Monitoring Regions

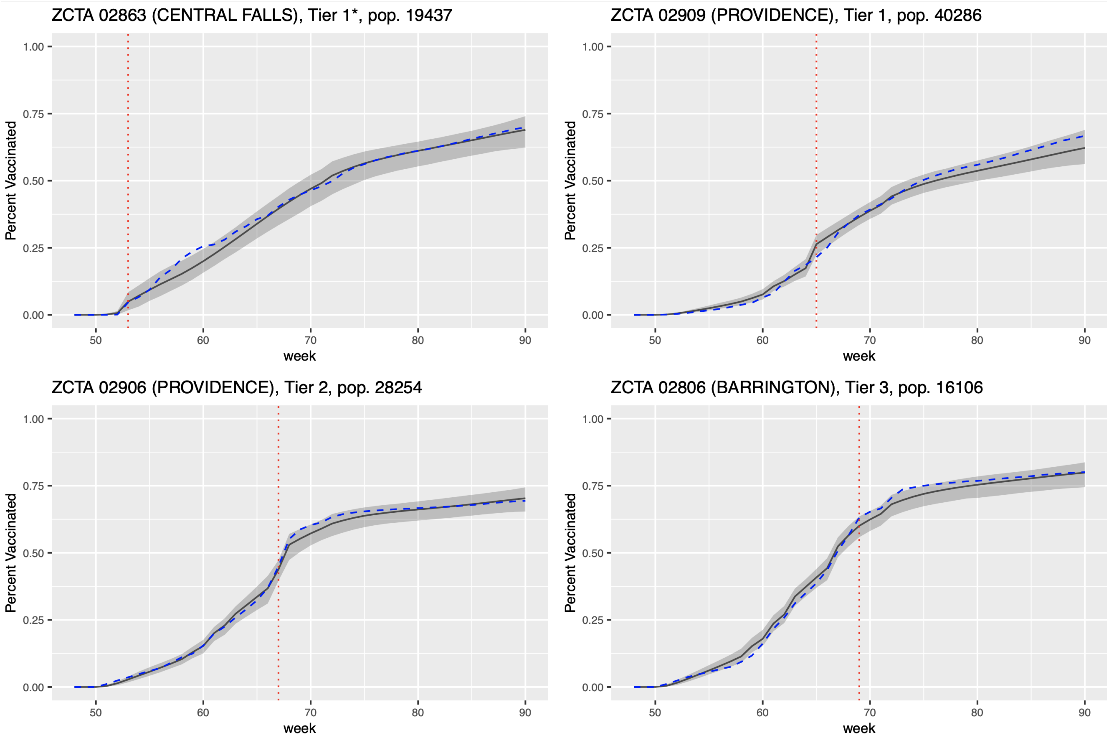
Because the Rhode Island Department of Health (RIDOH) 3-tier community risk classification system was defined by zip code tabulation area (ZCTA), and geographic vaccine prioritization was specific to these tiers, we began with ZCTA-level data, but needed to address small ZCTAs, for which population counts tended to be unreliable. Communities were excluded from the study if (1) census population count data proved unreliable, as was the case for one community, or (2) there was an identified reason for a highly fluctuating population in 2020 and 2021 (e.g. a large percentage were temporary residents, such as college students), as was the case for three communities. We used crosswalk files to determine component ZCTAs and attribute a ZCTA to the municipality that contained the largest proportion of the ZCTA when a ZCTA crossed municipal boundaries. In cases when the area name in the crosswalk file did not correspond to a distinct municipality listed in RIDOH's data (this was common in the case of census-designated places), the ZCTA was included as a part of the nearest defined municipality. In cases where a ZCTA was identified in the HUD crosswalk file but was not in the list of 77 ZCTAs maintained by RIDOH, the ZCTA was discarded. For any municipality containing a ZCTA with an estimated population size less than 1,000, we summed over the component ZCTAs. This criterion applied to 12 ZCTAs within 8 municipalities, which together included 24 ZCTAs overall, resulting in 61 monitoring regions (8 municipalities and 53 ZCTAs).

Next, we omitted four additional monitoring regions due to discrepancies in population counts or other issues: (1) one ZCTA in Providence (02912) with ACS-estimated population size of 1,360 because this ZCTA is administratively assigned to Brown University, and therefore does not correspond to a well-defined residential population; (2) one ZCTA in Newport (02841) with estimated population size of 1,792 because it is contained within a naval station and therefore appears to have unreliable vaccination counts; (3) one ZCTA in South Kingstown (02881) with estimated population size of 7,593 which is administratively assigned to the University of Rhode Island, and therefore also does not correspond to a well-defined residential population; and (4) New Shoreham, the municipality comprising all of Block Island, because we determined that the ACS estimate for the population size of this region (871 residents) was not reliable.

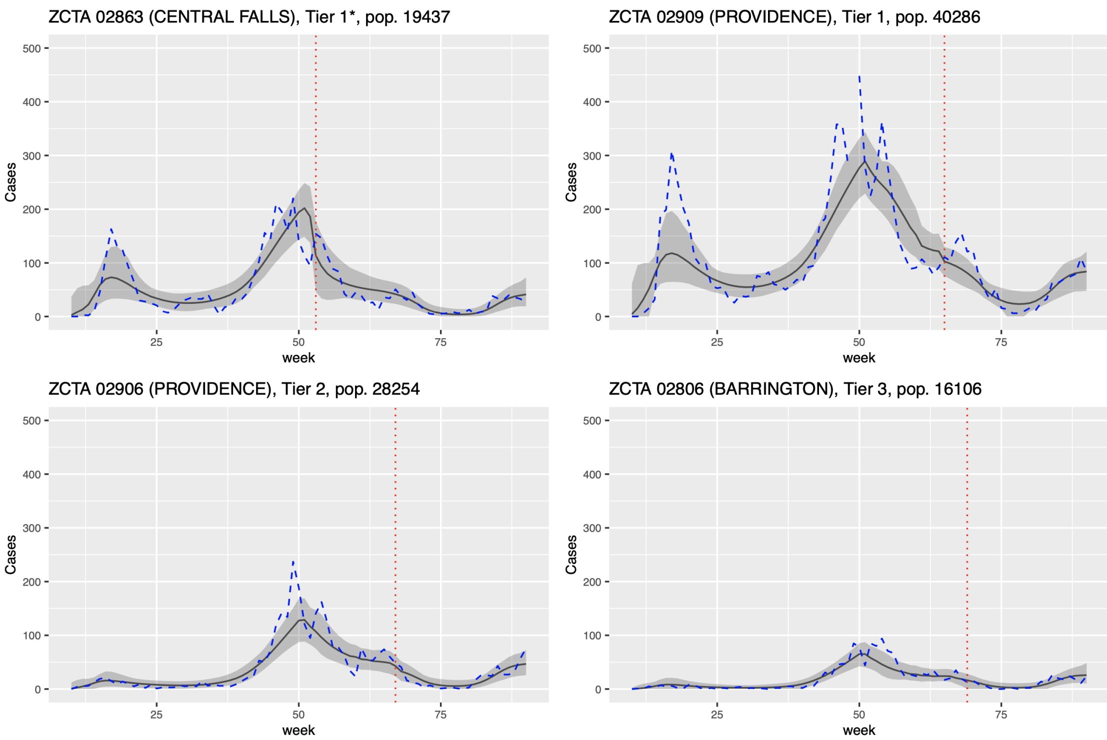
Following these modifications and exclusions, we analyzed 57 distinct monitoring regions: 7 municipalities and 50 ZCTAs (referred to as "communities"). Although using more granular subgroups, such as age groups within each municipality, may have enabled more precise representation of vaccine eligibility, the 2018 ACS population estimates were no longer valid for many age groups within some municipalities at the time of the analysis, making it difficult to take this approach. Of note, vaccine doses administered and reported cases for which ZCTA information was unknown or missing were discarded.

A.3 Figures Displaying Model Fit and Potential Outcomes by Community

In Appendix Figure A1, we provide examples of model fit with credible intervals for uptake and case count curves to summarize the fit of our models for four communities, one representative from each of the four realized eligibility strategies. Appendix figure A2 shows the potential outcomes under each of the four eligibility strategies for the same four communities.

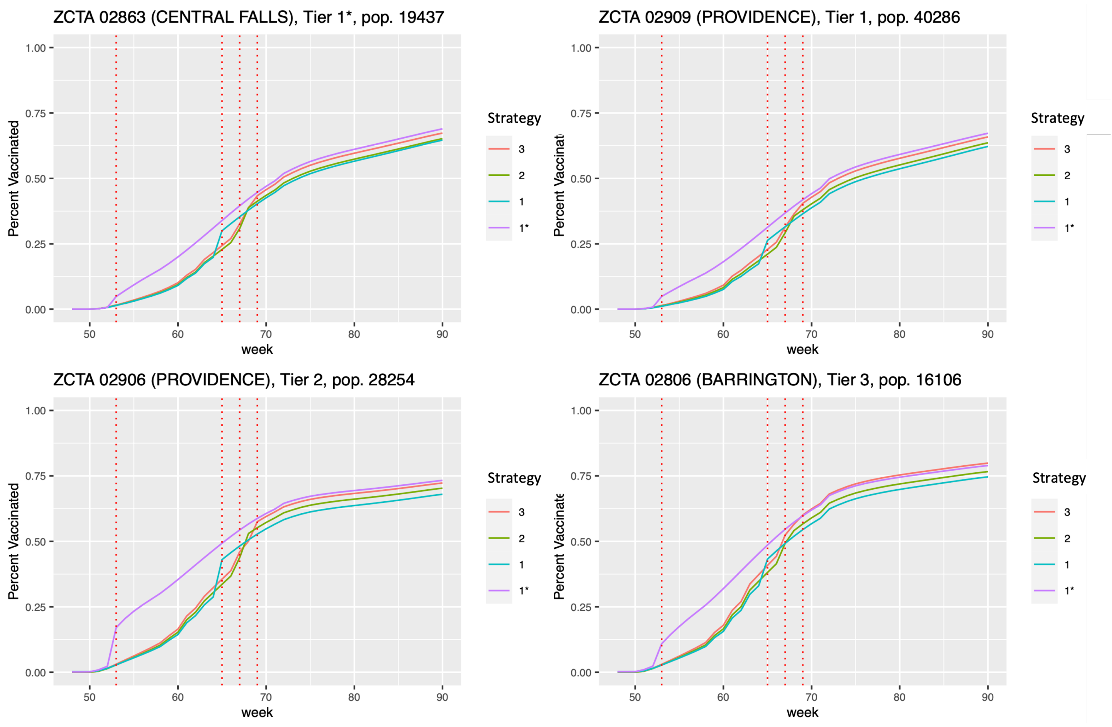


(a) Uptake curves for four communities. The horizontal axis spans 11/22/2020 (Week 48) - 9/18/2021 (Week 90).

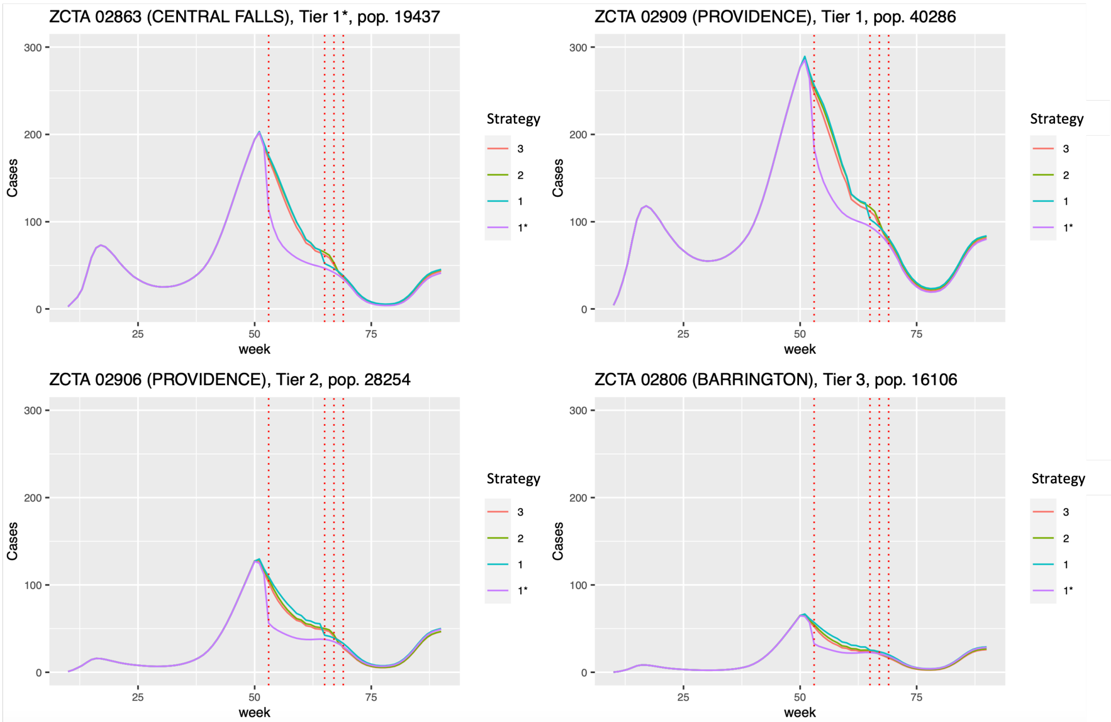


(b) Case counts for four communities. The horizontal axis spans 3/1/2020 (Week 10) - 9/18/2021 (Week 90).

Figure A1: In each panel, the blue dashed line indicates the observed values for that community, while the black curve indicates fitted values drawn from the posterior predictive distribution estimated by our modeling strategy. The red dotted lines indicate the timing of full adult eligibility in each community.



(a) Predicted vaccine uptake for four communities under the four different eligibility strategies. The horizontal axis spans 11/22/2020 (Week 48) - 9/18/2021 (Week 90).



(b) Predicted recorded case counts for four communities under the four different eligibility strategies, each based on the intermediary predicted draws for vaccine uptake shown in panel (a). The horizontal axis spans 3/1/2020 (Week 10) - 9/18/2021 (Week 90).

Figure A2: In each panel, the four colored lines indicate the posterior predicted mean of vaccine uptake (panel (a)) or case counts (panel (b)) under each of the four eligibility strategies. The red dotted lines indicate the timing of full adult eligibility under each of the four strategies.

A.4 Potential Alternative Strategies: Tier 1 Communities

As displayed in Figure 2, prioritizing all Tier 1 or all Tier 2 communities in aggregate could have reduced case rates into the range of those recorded in Tier 3 communities. In Figure A3, we display similar results for each Tier 1 community, indicating that prioritization of any of these could have reduced case rates to an equitable level.

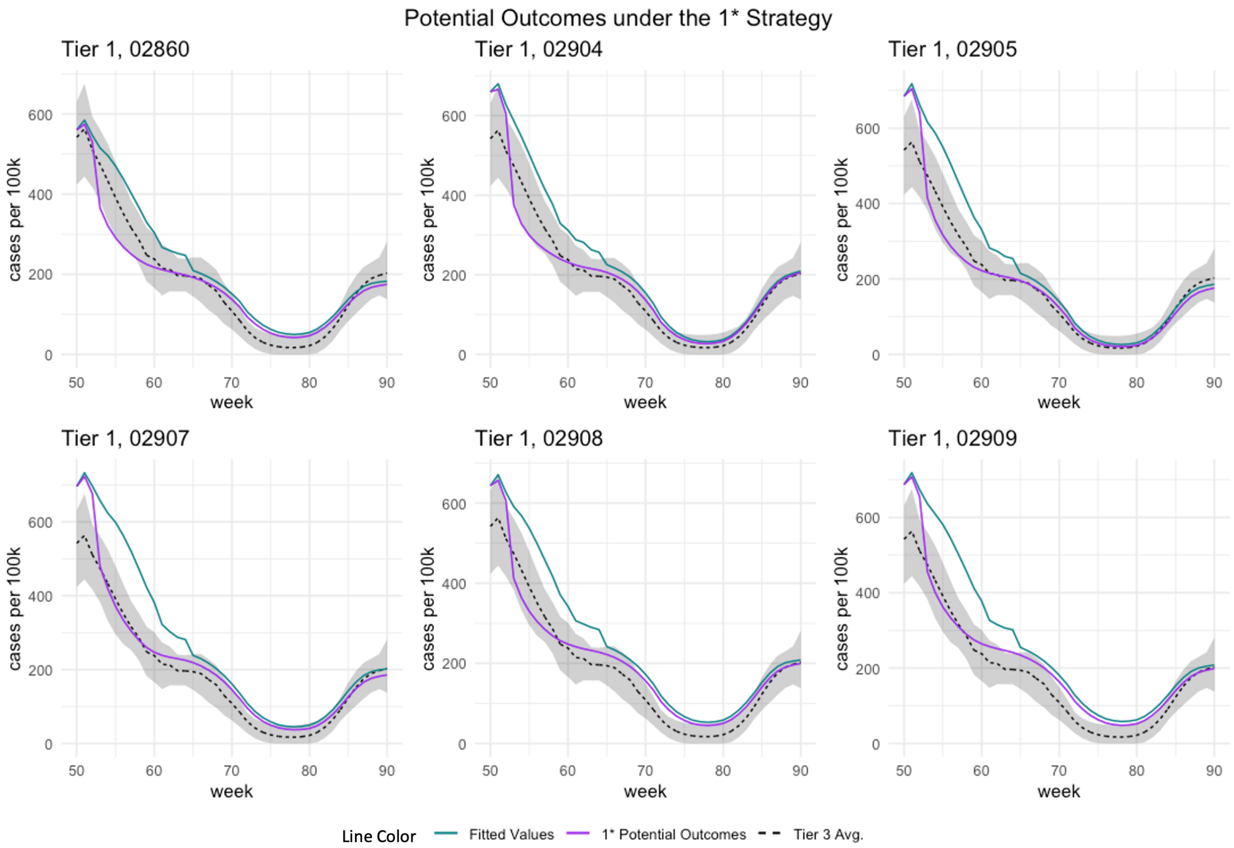


Figure A3: Another realistic alternative strategy would have been to prioritize any single Tier 1 community. Each panel of this figure suggests that the Tier 1* strategy would have rapidly reduced case rates to a more equitable level (i.e. in the range of what Tier 3 communities were experiencing) in each Tier 1 community. The purple line in each panel shows the potential recorded case counts per 100,000 population, if the indicated community had been prioritized as early as Central Falls (Tier 1* strategy). The turquoise line shows the fitted recorded case counts per 100,000 population under the Tier implemented strategy. The black dashed line shows the posterior mean and the shaded region the 95% density interval for the Tier 3 communities in aggregate. Tiers refer to the 3-tier community risk classification system developed by RIDOH to help guide COVID-19 surveillance and response efforts. Tier 1 included communities at highest risk of COVID-19 and Tier 3 included communities at lowest risk (see Section 2.1).

A.5 Additional Detail on Geographic Vaccine Prioritization Strategies

A.5.1 General Vaccine Prioritization Strategies

In the US, when COVID-19 vaccines first received approval in 2020, most jurisdictions implemented prioritization strategies based primarily on age, occupation, and chronic conditions[1] as recommended in federal guidelines at the time.[2] The primary concerns during this early phase of the pandemic were typically reduction in hospitalization risk, so as not to exceed hospital capacity, and reduction in mortality.[2] Thus, those at highest risk of severe illness and death were typically prioritized first, along with health care workers.[1,3] More than half of COVID-19 vaccine prioritization plans in US states did not incorporate input from a health equity committee.[4] Studies have suggested that other prioritization strategies may have been more effective for reducing mortality and improving health equity. A prior simulation study[5] compared each of four alternative COVID-19 vaccine distribution scenarios to a purely age-based strategy, using a simulation-based approach. They selected census tracts to prioritize by ranking tracts according to COVID-19 mortality rates and estimated varying likelihoods of getting vaccinated depending on eligibility and age group, assuming that those in prioritized census tracts would become a fixed percentage more likely to get vaccinated following eligibility.[5] They found that the purely age-based strategy increased racial and ethnic disparities in COVID-19 mortality, while strategies that prioritized vaccines by both geography and socioeconomic characteristics would have decreased racial/ethnic disparities and prevented more deaths overall, because of the higher risk of mortality among younger individuals in prioritized census tracts compared to elsewhere.[5] Another study, conducted in Norway,[6] which also used a simulation-based approach found that prioritizing vaccine doses to regions with high infection rates, found that although optimal strategies depended on the endpoint (i.e. infections, hospitalizations, ICU admissions, or fatalities), the optimal strategy for reducing infection rates was a strategy that prioritized geographic regions experiencing the highest infection rates.[6]

A.5.2 Features Motivating Geographic Vaccine Prioritization in Rhode Island

In the context of limited vaccine supply, the decision to prioritize all adult residents of Central Falls for early eligibility was based on multiple considerations, including:

- Disproportionately high COVID-19 cases, hospitalizations, and deaths, overall and among young people, even relative to other Tier 1 communities
- A high percentage of minority and undocumented residents (e.g., nearly 70
  - Potentially contributing to increased vaccine hesitancy and increasing the importance of linguistically- and culturally-appropriate outreach
  - Age-adjusted rates of cases, hospitalizations, and death were substantially higher among Hispanic/Latino and Black people compared to White people
- High population density, increasing risk of transmission
- Pre-existing structural policies and inadequate systems that perpetuate health inequities, such as a lack of health infrastructure, that would impact access to vaccines
- Relatively small population size (roughly 16,000 adults), making it feasible to prioritize all adult residents under vaccine supply constraints

Importantly, the public health rationale for prioritizing Central Falls earlier than those with underlying conditions statewide explicitly took into account not only the individual-level risk factors for severe outcomes (e.g., age, chronic conditions) but also the community-level risk more holistically. In this case, structural factors put the entire community of Central Falls at increased risk of exposure (and, thus, ongoing transmission), including barriers to staying home when lock down was recommended (e.g., essential/front-line workers), barriers to staying home from work when sick or to avoid colleagues who were sick (e.g. lack of paid time off), increased likelihood of carpooling to work, reduced ability to truly isolate when household members were sick (e.g., household crowding), increased likelihood of multi-generational households exposing immunocompromised people of all ages and elders, reduced access to mitigation measures (e.g., testing, physical distancing), and a high prevalence of chronic health conditions due to existing inequities (e.g., obesity, hypertension, diabetes). Additionally, the extensive COVID-19 transmission that was occurring in Central Falls was a very concerning risk factor for the surrounding communities and state as a whole. The population of Central Falls was relatively small (roughly 16,000 adults), also making prioritization feasible in the context of limited vaccine supply. In contrast, some individuals (e.g., older adults, those with certain chronic conditions) have a high risk of negative outcomes if exposed and infected but potentially less risk of exposure as a group compared the community of Central Falls overall. Furthermore, the most vulnerable people in areas with greater exposure risk are best protected by a community approach rather than just vaccinating the individual. Importantly, the State of Rhode Island had a COVID-19 Vaccine Advisory Sub-Committee, comprised of healthcare professionals in communities across Rhode Island, who reviewed the strategy and agreed with the prioritization. Central Falls was prioritized first in December 2020, with plans to expand eligibility to other Tier 1 communities as vaccine supply was available.

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B Appendix: Model specification and methods for inference

This section first provides some motivation for our modeling approach using Bayesian causal models, including a summary of potential alternative choices for analysis. We then give a brief description of the statistical model used to generate analyses in the paper. The overall model comprises two components: one for vaccine uptake, denoted by U, and a second for case counts, denoted by Y. In brief, at each week t and for each community j, vaccine uptake is a modeled as a function of (i) percent of the population for community j that is eligible for the vaccine and (ii) community-level covariates. Next, the community-specific recorded case count for that week is modeled as a function of vaccine uptake and community-level covariates. The component models themselves are fitted using Bayesian additive regression trees (BART) to ensure maximum flexibility in specification. BART is a Bayesian machine learning model, but because it is based on a probability model, it can be used to generate model-based predictions that are used for our comparison of case counts and case rates under different eligibility strategies.

B.1 Potential Alternative Modeling Approaches

Mechanistic models, such as susceptible-infectious-recovered (SIR) and other compartmental models, have been used to explore the potential impact of prioritizing specific groups for early receipt of SARS-CoV-2 vaccines.[1–4] In practice these models tend to require strong structural and parametric assumptions, such as constant vaccine availability over time[2,4] and uptake of all allocated vaccine doses,[2] that can limit the generalizability of the conclusions and do not allow for characterizing vaccine effects on a localized scale (e.g. vaccine uptake may differ substantially by community). Further, most models of this type require parametric assumptions concerning the dynamics of COVID-19 that limit their utility for small sub-populations (we do not have community-specific estimates of parameters governing infection spread), or rely on using parameter values estimated in different populations, both of which can introduce bias.[5] Rather than impose community-specific assumptions that could be incorrect when trying to estimate community-specific impacts, our approach is to model these effects directly from observed data.

Another standard policy evaluation technique used for assessment of a policy intervention is the difference-in-differences (DiD) method. DiD leverages information on the timing of an intervention to create pre- and post-intervention periods for multiple groups and compare the degree to which the trajectories of each group diverge following the intervention. However, DiD relies on several assumptions that that are likely to be unmet in our application. Notable among these is the 'parallel trends' assumption that endpoint trajectories of different communities are parallel prior to the intervention.[6] The non-linearity and differential timing of key inflection points evident in Figure 1 strongly suggests that the parallel trends assumption would not be met. Additionally, emerging research[7] has shown that using DiD to model incident case numbers may produce biased effect estimates due to unequal initial infections and transmission rates between groups.

An approach that does not rely on parallel trends is the method of synthetic controls (SCM),[8,9] in which control units are used to estimate the counterfactuals for treated units. In general, this approach requires specifying the functional form for time trend among controls, using weighted contributions from control units to estimate the trends and produce counterfactual estimates. However, the temporal trends in the Rhode Island data differ substantially by community. This motivated our use of Bayesian additive regression trees (BART), which does not require a common trend among control units and allows us to leave the function for community-specific temporal trends to be left unspecified and learned using the data. Moreover, Callaway et. al.[10] show that applying SCM is not straightforward in the context of an underlying non-linear disease generating process. Other work in progress suggests that SCM may produce unreliable estimates of policy effects, even providing a well-fitting synthetic control in the pre-intervention period, specifically showing that, assuming an underlying SIR model, constructing synthetic controls using incident counts or rates will produce biased treatment effects unless the treated unit and all comparison units with non-zero weights have identical transmission parameters and initial conditions. If not, the treatment and synthetic comparison groups will diverge, even if they match in the pre-intervention period. As a result, given the strength of this assumption, we are hesitant to use this method in the context of disease transmission without further research and refinement.

Neither DiD nor SCM offers a natural way to model the impact of the policy through a two-stage process that incorporates a model for the impact of the policy through the vaccine uptake intermediate endpoint, which was structurally equal to zero in every community prior to implementation of the policy.

Finally, we use a Bayesian machine learning approach in order to account for a large set of potential confounders and produce a model that allows us to simulate from the posterior distribution, while modeling the data-generating process and minimizing the potential for mis-specification bias attributable to incorrectly specifying the precise functional relationship between outcomes and confounders.[11] We specifically chose SoftBart because it allows us to flexibly capture the irregular time trends[12] in case counts by community. For these reasons we proceed with a Bayesian causal modeling approach to evaluating this policy.

B.2 Notation and Variable Definitions

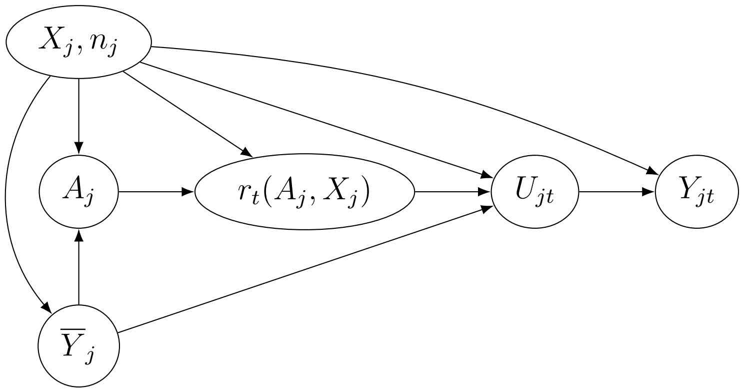
Here we use notation and definitions for the variables used in the component models. We index time in weeks using t, where $t = 10, 11, \ldots, 90$ are weeks corresponding to the period 1 March 2020 to 18 September 2021, beginning by numbering weeks according to the MMWR convention and continuing with consecutive numbering into 2021, rather than returning to Week1.Weuse$j$ to index community, where $j = 1, \ldots, 57$. We then define the following variables:

$$
\begin{aligned}
U_{jt} &= \text{cumulative vaccine uptake in community } j \text{ at week } t, \\
&\quad \text{defined as percent receiving at least one dose of any COVID-19 vaccine} \\
Y_{jt} &= \text{number of recorded cases in community } j \text{ during week } t \\
r_{jt}(a) &= \text{percent of the population in community } j \text{ who are eligible} \\
&\quad \text{for vaccination during week } t \text{ under the restrictions} \\
&\quad \text{corresponding to eligibility strategy } a \\
a &= \text{eligibility strategy label, defined by tier} \\
&\in \{1^*, 1, 2, 3\} \\
A_j &= \text{actual eligibility strategy applied to community } j \\
X_j &= \text{vector of sociodemographic variables for community } j \\
n_j &= \text{population size of community } j \\
\overline{Y}_j &= \text{pre-vaccine recorded case rate in community } j
\end{aligned}
$$

Note that the percent eligible, $r_{jt}(a) = r_t(a, X_j)$, is a deterministic function of an eligibility strategy a and the community-specific covariates X_j. For a given strategy a, $r_{jt}(a, X_j)$ can be computed directly from X_j. For example, if strategy a indicates that eligibility is restricted to those over 65, information in X_j about the age distribution would be used to calculate the fraction of the population over 65. Note also that while (lower case) a is a label for strategies, (upper case) A_j represents the strategy that actually was applied to community j. The policy, while not time-varyng itself, imposes time-specific dates for eligibility among certain subsets of the population. Hence $r_{jt}(A_j)$ is indexed by t and denotes the fraction that actually were eligible for vaccination in community j at time t.

B.3 Causal Framework

The directed acyclic graph (DAG) below depicts the causal structure and assumptions underlying our model. A key assumption that we make is that the impact of the eligibility strategy on case counts operates solely its impact on uptake of the vaccine.



Based on the DAG, we can write the assumptions of an underlying causal structural model in terms of potential outcomes for Y and U. Based on these assumptions, we can use the observed data model to generate simulate counterfactual outcomes for U and Y under fixed values for the policy. For example, even though Central Falls was prioritized for early vaccine eligibility, with $A = 1^*$, we can use the observed-data model to generate counterfactual predictions of vaccine uptake and case counts under the assumption that a different strategy would have been applied to Central Falls; i.e., if $A = 3$. A comparison of potential outcomes under $A = 1^*$ and $A = 3$, drawn from the apppropriate posterior predictive distributions, yields an inference about the impact of applying strategy 1*. Specifically, it yields a comparison of what happened under strategy $A = 1^*$ versus what *would have happened* under policy $A = 3$.

Our causal model relies on the following assumptions:

(A1) No unmeasured confounders for vaccine uptake. We assume that potential cumulative vaccine uptake $U_{jt}(a)$ is independent of prioritization strategy A_j conditional on X_j, n_j, and $\overline{Y}_j$. Specifically we assume that for community j and for $t = 10, \ldots, 90$,

$$U_{jt}(a) \perp\!\!\!\perp A_j \mid X_j, n_j, \overline{Y}_j.$$

In words, this implies that, conditional on demographic covariates, population size, and case counts prior to vaccine availability up, vaccine uptake that would have been observed under strategy a is independent of the strategy A_j actually assigned. Another way to represent this assumption is to say that for communities having the same observed history X_j, n_j and $\overline{Y}_j$, the assignment of eligibility strategy A can be viewed as a randomized assignment.

(A2) No unmeasured confounders for case counts. We assume that potential case count $Y_{jt}(a, U_{jt}(a))$ is independent of the observed vaccine uptake, conditional on demographic covariates X_j and n_j. Additionally we assume that potential case count is independent of prioritization strategy A_j conditional on vaccine uptake and community-level covariates. Specifically we assume that for community j and for $t = 10, \ldots, 90$,

$$\begin{aligned} Y_{jt}(a, U_{jt}(a)) \perp\!\!\!\perp U_{jt} \quad &\mid \quad X_j, n_j \\ Y_{jt}(a, U_{jt}(a)) \perp\!\!\!\perp A_j \quad &\mid \quad U_{jt}, X_j, n_j \end{aligned}$$

(A3) Positivity. This assumption requires that every community has a positive probability of receiving each treatment, or that

$$P(A_j = a \mid X_j) > 0$$

for all $a \in \mathscr{A}$ and for all possible realizations of X_j. In the context of this application, we conduct the analysis under the assumption that every community could have received each intervention; in reality, vaccine supply limitations would have prohibited all communities from receiving vaccine prioritization all at once. When simulating potential outcomes under distinct policies a, we look at the impact of the policy only for communities that plausibly could have received the specific intervention.

(A4) Stable Unit Treatment Value Assumption (SUTVA). This assumption requires that the potential outcomes for one community do not depend on the treatments assigned to others. In practice this assumption is not likely to hold across the entire state. Eligibility for vaccination in one community may have an impact on a neighboring community because protection from a vaccine impacts the infection probability of those who come into contact with the vaccinated person. We recognize that the potential for geographic 'spill-over', which we plan to address in a future analysis.

B.4 Predictors

The variable describing percent of the population of a community eligible for vaccination at a given time $r_{jt}(A_j)$ was used in conjunction with variables describing community-level demographics X_j (described in detail in Section 2.2.3), case history $\overline{Y}_j$, and time to produce a model for vaccine uptake. Vaccine uptake $U_{jt}(A_j)$, measured as the cumulative percent of the population of a given community who had received at least one dose of a vaccine by a given week, was used alongside sociodemographic covariates X_j and time to model case counts.

We adjust for sociodemographic covariates in order to account for community characteristics considered by RIDOH when making vaccine allocation decisions. Collider bias typically (but not always) arises in settings where the observations are sampled based on an outcome (e.g., drawing a sample of individuals who have tested for COVID, or who have been hospitalized for COVID). While we would not completely rule it out, we could not identify an obvious source of collider bias in our model.

As with any causal model of observational data, unmeasured confounding is a concern.

Based

on our DAG, the most obvious source of unmeasured confounding are variables that would confound the assumed causal relationship between vaccine uptake U and case count Y for a specific geographic area. Perhaps the most obvious source of potential unmeasured confounding is individual behavior that is not explained by the variables in X_j. For example, if individuals who are more likely to use non-pharmaceutical measures such as masking or avoiding indoor public spaces are both more likely to get vaccinated and less likely to become infected with COVID, and if this pattern manifests at the community level, the impact of the vaccine would be under-estimated by our model. We recognize this and other possible unmeasured confounding mechanisms as a limitation in the discussion.

B.5 Model Specification

We begin by modeling vaccine uptake U_{jt}, or the proportion of the population who has received at least one dose of vaccine, as a function of time, demographics, assigned strategy, and community. The first authorized COVID-19 vaccine did not receive an Emergency Use Authorization until December 11, 2020 (week 51 in our numbering). Therefore, the data contain structural zeros for U_{jt} from weeks 10-50. Instead of modeling U_{jt} directly, we specify our model using a probit transformation $U^*_{jt} = \Phi^{-1}(U_{jt})$, where $\Phi(\cdot)$ is the CDF of the standard normal distribution $\mathscr{N}(0,1)$. To handle varying population sizes of communities (range 2,194 to 47,175), we used variance weights proportional to $n_j^{1/2}$.
We specify the model for U^*_{jt} as follows,

$$U^*_{jt} \mid X_j, A_j \sim \mathscr{N}(f_U(t, X_j, \overline{Y}_j, r_{jt}(A_j); \theta_U),\ n_j^{1/2}\sigma^2_{jt}),$$

where the mean function $f_U(t, X_j, \overline{Y}_j, r_{jt}(A_j); \theta_U)$ is an unspecified function of its arguments and indexed by a parameter θ_W that is described below. Because the function is expected to be a relatively smooth but nonlinear function of time, we use SoftBART to impose smoothness across the domain of t. BART itself is a Bayesian sum-of-trees model, where regularization is achieved by specifying f as a sum of a large number of shallow trees.[11,12] Parameters governing tree depth and probability of node-splitting characterize the tree structure; priors can be used to calibrate model complexity and smoothness. More details are given below.

For the case counts, we use a mixture model to accommodate periods of time where community-specific counts reach zero. Specifically, we write the observed case count Y_{jt} as

$$Y_{jt} = (1 - Z_{jt})W_{jt},$$

where $Z_{jt} = \mathbb{I}\{Y_{jt} = 0\}$ is an indicator of whether the case count is equal to zero (1 if yes, 0 if no) and W_{jt} is the number of cases when the case count is nonzero. Using exploratory data analysis and goodness-of-fit assessments, we found empirically that $W_{jt}^{1/2}$ is well approximated by the normal distribution, which motivates our model choice.

This zero-inflated model is specified in two parts, one for Z_{jt} and the second for $W_{jt}^{1/2}$,

$$\begin{aligned} Z_{jt} \mid X_j, U_{jt} &\sim \text{Bernoulli}(\pi_{jt}) \\ W_{jt}^{1/2} \mid X_j, U_{jt} &\sim \mathcal{N}(f_W(t, U_{jt}, X_j; \theta_W),\ n_j^{1/2}\tau_{jt}^2). \end{aligned}$$

The model for Z_{jt} uses a probit specification where

$$\Phi^{-1}(\pi_{jt}) = f_Z(t, U_{jt}, X_j; \theta_Z).$$

As with the model for vaccine uptake, the functions f_Z and f_W are left unspecified and the models are fit using SoftBart.[13] Prior parameters were specified at their defaults to promote smoothness of predicted values and avoid overfitting.

B.6 Posterior Predictive Distributions to Compare Eligibility Strategies

A major advantage of using BART (or any Bayesian modeling approach) in this setting is that fitting each of the models described above yields posterior distributions for the model parameters, which can then can be used to generate posterior predictive distributions of the outcomes under different covariate configurations. The posterior predictive distributions of the outcomes are simulated realizations of vaccine uptake and case counts that are generated from the fitted model and that fully account for the uncertainty in the parameter estimates. Dropping subscripts for clarity, the posterior predictive distribution for case counts under eligibility strategy a can be written heuristically as

$$p(Y \mid X, A = a, \text{Data}) = \int p(Y \mid U, X, A = a, \theta_W, \theta_Z, \sigma)\, p(U \mid X, A = a, \overline{Y}, \theta_U, \tau)\, p(\theta \mid \text{Data})\; dU\; d\theta, \quad (1)$$

where $\theta = (\theta_Z, \theta_W, \theta_U, \sigma, \tau)$, $p(\theta \mid \text{Data})$ is the posterior distribution of the model parameters, and $p(Y \mid U, X, A = a, \theta_W, \theta_Z)$ represents the mixture distribution described above. In short, we set the eligibility strategy to $A = a$ in each of the models, simulate a predicted value of vaccine uptake $U(a)$ for strategy a, and for that specific uptake we simulate case count Y. Under the 'no unmeasured confounders' assumption we can interpret these posterior predictive draws as realizations of $Y(a, U(a))$, which is the potential outcome (or counterfactual) that would have been observed had the community been assigned eligibility strategy a. This assumption requires that for $a \in \{1^*, 1, 2, 3\}$, $U(a)$ is independent of A conditional on X and $\overline{Y}_j$, and that $Y(a, U(a))$ is independent of A conditional on X and $U(a)$. These assumptions imply

$$\begin{aligned} p(Y(a, U(a)) \mid U, X, \theta_W, \theta_Z) &= p(Y \mid U, X, A = a, \theta_W, \theta_Z) \\ p(U(a) \mid X, \overline{Y}_j, \theta_U) &= p(U \mid X, \overline{Y}_j, A = a, \theta_U), \end{aligned}$$

so that the posterior predictions in (1) can be interpreted as potential outcomes.

After fitting the models we proceed as follows to draw potential case counts $Y_{jt}(a, U(a))$ for each a and for all (j, t). To streamline notation, we write $Y(a, U(a))$ as $Y(a)$.

1. Draw $\tilde{\theta} \sim p(\theta \mid \text{Data})$

2. Draw $\tilde{U}^*_{jt}(a) \sim \mathcal{N}(f_U(t, X_j, \overline{Y}_j, r_{jt}(a), \tilde{\theta}_U), \tilde{\sigma}^2_{ij})$

3. Calculate percent vaccine uptake $\tilde{U}_{jt}(a) = \Phi(\tilde{U}^*_{jt}(a))$.

4. Using the vaccine uptake value $\tilde{U}_{jt}(a)$, calculate $\tilde{\pi}_{jt} = \Phi(f_Z(t, U_{jt}(a), X_j; \tilde{\theta}_Z)$ and draw $\tilde{Z}_{jt}(a) \sim \text{Bernoulli}(\tilde{\pi}_{jt})$.

5. Draw case count $\tilde{Y}_{jt}(a)$.

   (a) If $\tilde{Z}_{jt}(a) = 1$, then set $\tilde{Y}_{jt}(a) = 0$

   (b) If $\tilde{Z}_{jt}(a) = 0$, draw $\tilde{W}^{1/2}_{jt}(a) \sim \mathcal{N}(f_W(t, \tilde{U}_{jt}(a), X_j; \tilde{\theta}_W),\ n_j^{1/2}\tilde{\tau}^2_{jt})$, and set $\tilde{Y}_{jt}(a) = \tilde{W}_{jt}(a)$.

We use 6000 posterior predictive draws to compute causal effects for each strategy that was realized in a specific community to any other potential strategy that could have been applied and compare effects in this manner.

For example, to assess the impact of early eligibility for Central Falls, we compare the predicted number of cases under the observed strategy $a = A_j = 1^*$ to the predicted number under a different strategy, say $a = a' = 3$. Hence the comparison uses the contrast in posterior predictive distributions given by $p(Y(1^*) \mid \text{Data})$ and $p(Y(3) \mid \text{Data})$.

Importantly, in our comparisons between strategies, we only generate predicted potential case counts under eligibility strategies that could plausibly have been used for a specific community. For example, for Central Falls – which received eligibility strategy 1^* – we also calculate predicted case counts for strategy 3 because using this strategy was among the plausible options when rolling out the vaccine statewide. However, our inferences about policy effect do not include scenarios where (for example) Tier 3 communities like Barrington would have received vaccines under strategy 1^*. These scenarios were not plausible because vaccine availability was limited at the time the rollout was taking place.

B.7 Brief Description of Bayesian Additive Regression Trees (BART)

Our predictive models need to accommodate the highly nonlinear and heterogeneous nature of trends in case counts and vaccine uptake, and to incorporate a large number of community-level predictors that impact these endpoints. Pre-specifying the functional form for the models is challenging at best and likely prone to model mis-specification (for example by failing to include important interactions or by mis-specifying the functional form of a covariate). Even the use of regression splines for time trends is difficult because the proper selection of knot points might differ by community.

BART is a highly flexible tree-ensembling approach to regression modeling (similar to random forest and boosting).[11] Consider modeling an outcome Y as a function of a vector of covariates $X = (X_1, \ldots, X_k)$. The BART specification is

$$Y = f(X) + \epsilon,$$

where $\epsilon \sim \mathscr{N}(0, \sigma^2)$ and the function $f : \mathscr{X} \to \mathbb{R}$, which maps a value $X \in \mathscr{X}$ to a scalar, is parameterized as a sum of J trees,

$$f(X; \mathcal{T}, \mathcal{M}) = \sum_{j=1}^{J} h(X, \mathcal{T}_j, \mathcal{M}_j).$$

In this notation, $h(X; \mathcal{T}_j, \mathcal{M}_j)$ denotes a regression tree function where the tree $\mathcal{T}_j$ encodes the leaf and branch nodes and $\mathcal{M}_j$ is the set of terminal node parameters (essentially the mean outcome for that partition). Thus each tree explains a portion of the systematic variation in Y.[11]

In order to prevent any one tree from influencing the model too heavily, BART uses prior distributions on the tree parameters; these regularize the overall model fit[12]. In short, the prior for the tree $\mathcal{T}_j$ parameterizes a branching process that grows the tree based on splitting probabilities and a pre-specified depth d. For SoftBart, the branching (splitting) probability at each node is $\gamma(1+d)^{-\beta}$. For a given depth d, the values of γ and β govern the structure of each tree. Full details are given in *SoftBart: Soft Bayesian Additive Regression Trees.*[12] The prior impacts the splitting rules for each tree by penalizing the branching probability dependent on depth, the terminal node parameters conditional on each tree to shrink these toward zero, and σ, informed by the data to allow reasonable probability across the range of possible values for σ to avoid overfitting by concentrating estimates at smaller values.[11] SoftBart is an implementation of BART that replaces regression trees with "soft regression trees," which use soft decision rules, assigning a probability at each node, to result in a continuous function at each split.[12] This allows SoftBart to generate smoother predictions. SoftBart models also use regularization priors, with parameters and hyperparameters selected to reduce the risk of overfitting.[12] We fit our models using default tuning parameter settings as described in the documentation for the `SoftBart` package.[13]

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