# Optimal COVID-19 Vaccination Facility Location under Heterogeneous Demand

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Socioeconomic disparities in COVID-19 vaccination rates are partly attributable to poor vaccination site selection, often requiring excessively burdensome travel distances. In early 2021, the U.S. government launched the Federal Retail Pharmacy Program (FRPP) to offer new access points, yet these pharmacies tend to locate in high-income, urban areas. We empirically examine how proximity to a vaccination site relates to uptake using cross-sectional data within California. Using Healthy Places Index (HPI)—a composite measure of a community's health—we find that the lowest HPI quartile residents are significantly more sensitive to distance than those in the top quartile. Halving the distance required to get vaccinated increases vaccinations by 5% in the lowest quartile, five-times the expected change in the top quartile. Panel data regression analyses confirm that reducing distance to a mass vaccination site *causally* increases vaccinations. Integrating our vaccination demand curves into a facility location model, we compute the change in distance to a vaccination site—and the associated gain in vaccination uptake—following optimal site selection. We expand the set of feasible locations to include dollar stores, which typically locate in lower-income communities hardest hit by the pandemic. Replacing 744 (18%) of the 4,035 existing pharmacies with optimally chosen dollar stores increases vaccinations by 1.5 million in California, including 530,000 in the bottom HPI quartile. Ignoring demand heterogeneity widens the vaccination gap, as resources shift to healthier and wealthier communities. Our study offers a quantitative framework to help policymakers with future vaccine allocation and access to boosters, particularly for marginalized populations.

*Key words*: COVID-19, vaccine access, demand estimation, facility location, socioeconomic disparities

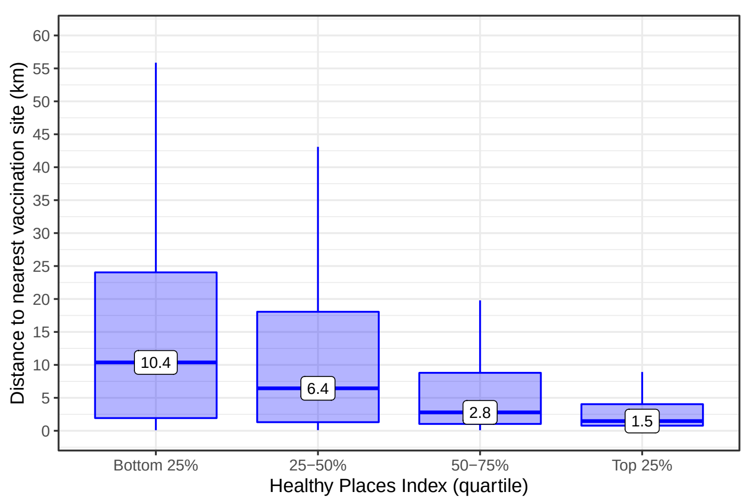
## 1. Introduction

Disparities in COVID-19 vaccination uptake have persisted since early 2021, particularly for booster shots, with sizeable differences observed by race (Ndugga et al. 2022), education level (Malik et al. 2020), urban/rural locale (Murthy et al. 2021), age (Lin et al. 2020), partisanship (Kates et al. 2022), and trust in the government and healthcare institutions (Moucheraud et al. 2021). Even before a vaccine against SARS-CoV-2 was available, individual attitudes varied widely, highlighting the multitude of reasons for vaccine hesitancy including concerns over safety and efficacy, anti-vaccine views, insufficient trust in the approval process, and a desire to wait for additional data (Fisher et al. 2020). Such concerns have resulted in lower vaccination rates, particularly among the most socially vulnerable populations (Crane et al. 2021).

Policy interventions aiming to increase vaccinations typically focus on one of three areas: better messaging (Chevallier et al. 2021), behavioral nudges (Dai et al. 2021), or improved logistics. Vaccination logistics includes healthcare worker training, vaccine storage and inventory management, mass vaccination site selection (Bertsimas et al. 2022) and operations. Seeking to expand COVID vaccination access points, in early 2021, the U.S. government launched the Federal Retail Pharmacy Program (FRPP), a partnership with 21 national pharmacy chains and independent pharmacy networks. As of June 2022, more than 253 million doses have been administered through FRPP, across 41,000 retail locations (CDC 2022).

A geospatial analysis found that half of all Americans live within one mile of a COVID vaccination site, and 89 percent live within five miles (Berenbrok et al. 2021). The required travel distance to a vaccination site, however, differs substantially across counties and by demographic group, with Blacks disproportionately more likely needing to drive at least ten miles to a vaccination site. These findings are perhaps unsurprising given the lack of retail pharmacies in rural areas (Hawryluk 2021, Salako et al. 2018) and predominantly Black and Hispanic neighborhoods (Guadamuz et al. 2021, Qato et al. 2014). A recent study of COVID vaccinations in Florida noted that Publix grocery stores—where one-quarter of all vaccinations were administered—are primarily located in higher income, older, and more White communities (Attonito et al. 2021). In California, the Healthy Places Index (HPI) is a composite measure of a community's well-being based on education, income, housing, and other social determinants of health (Public Health Alliance of Southern California 2022). Across the state, a major hurdle to get vaccinated is faced by the most vulnerable group: median distance to the nearest COVID vaccination site exceeds 10 km for residents in the bottom

**Figure 1** **Distance to the nearest vaccination site by Healthy Places Index in California**



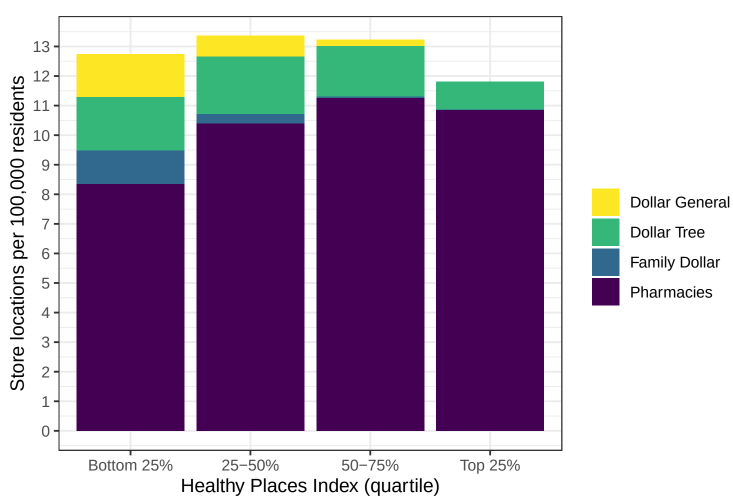

*Note.* Boxplot shows the distribution (25-50-75th percentiles) of Euclidean distance between each zip-code population centroid and the nearest FRPP pharmacy, with median values reported.

quartile of HPI, compared to 1.5 km for the top quartile (Figure 1). Additionally, more than 10% of households in the bottom HPI quartile lack access to an automobile, nearly double the rate in the top quartile (Public Health Alliance of Southern California 2022).

Realizing these challenges, the CDC director and one of the country's largest discount retailers, Dollar General, confirmed reports of a potential partnership to administer COVID-19 vaccines at store locations. Widely popular for discounted prices and product selection, much of Dollar General's success has arisen from locating in places with little competition from other retailers (Wolfrath et al. 2018). Dollar General operates more than 17,000 stores in 46 states (including 238 stores in California), nearly double the number of locations offering COVID vaccinations by the next largest private retailer, and 75% of its stores serve rural communities with fewer than 20,000 people (Bomey 2021, Roberts 2021). Two other discount chains, Dollar Tree and Family Dollar, each operate more than 7,000 stores nationwide (including 631 and 147 stores in California, respectively). Most importantly, these discount stores tend to locate in lower-income communities, precisely the areas most underserved by existing retail pharmacies (Figure 2), creating a promising opportunity to improve vaccination access for low-income households (Chevalier et al. 2022).

Since August 2021, Dollar General has joined health departments in California, Georgia, Kansas, Michigan, Ohio, South Carolina and Virginia to offer free vaccines to local residents by hosting clinics in their store parking lots. Through this effort, more than 5,300 vaccines were administered in 2021 (Dollar General 2021). Although the ubiquity of dollar stores provides a broad set of alternative vaccination sites, it remains unclear to what extent adding these retail stores to the current vaccination program might improve uptake or reduce disparities. With the transition to excess vaccine supply in the U.S., finding alternative distribution channels for unvaccinated groups will be essential to mitigating future pandemic waves.

**Figure 2** **FRPP pharmacy vaccination sites and dollar stores (by national chain) in California, by HPI quartile**



The facility location problem has been extensively studied in the OM literature and within the healthcare context (see Ahmadi-Javid et al. (2017) for a review), but limited research exists on optimally selecting vaccination sites during a pandemic. Basciftci et al. (2021) use robust optimization to select resource (*e.g.*, vaccines and test kits) distribution centers under disease transmission and demand uncertainties. Bertsimas et al. (2022) similarly combine a predictive compartmental epidemic model with a high-level optimization model to assign populations to 100 mass vaccination sites across the U.S., with results robust to epidemic forecasting uncertainty. Relatedly, Rastegar et al. (2021) consider a distribution and storage facility location problem with inventory decisions to equitably distribute influenza vaccines during the COVID-19 pandemic.

Risanger et al. (2021) examine equitable access to COVID-19 testing using an optimization model to maximize the number of individuals tested at their closest pharmacy and find that if COVID-19 testing was offered at all U.S. pharmacies, 94% of Americans would be within short distance of a testing site. This is a best-case scenario as testing site capacity is omitted and a homogeneous willingness-to-travel function is estimated using transportation data rather than testing data. Most related to our current study, Chevalier et al. (2022) calculate the distance to the closest vaccination site under FRPP and after hypothetically adding all Dollar General stores in 21 states. Using retail pharmacies exclusively provides a vaccination site within five miles of most Americans, but adding Dollar General stores would considerably reduce distances, particularly for low-income and minority households. Our work differs in that we explicitly estimate a heterogeneous vaccine demand function and formulate a math program to *optimally select* vaccination sites with limited capacity to maximize predicted vaccinations.

Several other empirical OM papers examine COVID-19 policies related to vaccination, testing, and social distancing. Serra-Garcia and Szech (2022) experimentally show that payment incentives increase stated intentions to be vaccinated and tested, and they document which groups are most responsive to these measures. Using state-level vaccine allocation and mobility data, Zhong et al. (2021) estimate that a one percent increase in COVID-19 vaccinations led to a 0.68% increase in public transit mobility, and the authors advocate for governments and transit agencies to revitalize public transportation in advance of demand recovery. Using smartphone location data, Carranza et al. (2022) estimate the heterogeneous impact of social distancing orders on mobility and the predicted effect on new cases. They find that social distancing effectiveness varies significantly by socioeconomic status, with larger reductions in higher-income communities. Similarly, Wang (2022) compare U.S. states with and without stay-at-home orders and find that such mandates reduce new cases by 8% through reduced visits to grocery stores, retail locations, etc. In a related study, Wang (2021) find that stay-at-home orders are less effective in counties with more uninsured or less educated residents, as the orders are less useful at reducing essential work-related trips.

In this paper, we investigate the heterogeneous effect of vaccination site proximity on uptake, and propose an alternative distribution channel—the use of dollar stores—to reduce vaccination inequalities. Our proposed facility location model identifies the optimal set of vaccination locations, without increasing the total number of sites, and quantifies the improvement in vaccination rates by socioeconomic group. The main contributions are as follows:

- Using cross-sectional data on COVID vaccinations by zip-code in California, we empirically examine the relationship between distance to a vaccination site and vaccination uptake, allowing for heterogeneous demand functions. These distance elasticities vary significantly by the Healthy Places Index (HPI), with less healthy/wealthy populations being much more sensitive to distance requirements. Halving the distance to a vaccination site from 2 km to 1 km, for example, is associated with nearly a 5% higher vaccination rate for the lowest HPI group and a minimal change for the highest HPI group. Panel data regression analyses confirm our main findings, but may be less generalizable as fewer vaccinations occurred at mass dispensing sites. Our study is the first to document a significant relationship between proximity to vaccination locations and uptake.
- Combining our estimated vaccination demand curves with a facility location model, we quantify the improvement in vaccine uptake with optimally selected vaccination sites using California as a test case. Expanding the feasible set of vaccination locations to include dollar stores, we optimally assign 8,000+ census tracts to one or more of the 5,000+ candidate sites using a mixed-integer program. To our knowledge, our study is the first to propose a data-driven mechanism to reduce disparities in COVID-19 vaccination access using a facility location optimization model.
- Solving the model using real store location and demographic data for California, the optimal solution replaces 18% of existing pharmacy vaccination sites, which tend to locate in higher-income areas, with dollar stores. This theoretically results in 1.5 million additional vaccinations, with more than one-third accruing to the lowest HPI group. Across the state, average distance to a vaccination site drops by 13%, and by 21% among the lowest HPI areas, significantly reducing inequalities, demonstrating how dollar stores could augment the existing network of pharmacy partners offering COVID vaccination. If we ignore our heterogeneous distance elasticities, the optimal solution shifts store locations to high HPI areas, further widening the vaccination gap by 5 percentage-points.

## 2. Demand Estimation

Despite observational evidence linking closer proximity to a COVID vaccination site with higher vaccination uptake (Berenbrok et al. 2021), no prior study has empirically tested this hypothesis. Here, we empirically estimate the relationship between distance to a vaccination site and vaccination rates—a *distance elasticity*—controlling for key demographic covariates. Our empirical approach is twofold. First, we use cross-sectional data on vaccination rates by geographic area to examine whether distance to a FRPP pharmacy is predictive of vaccination rates, and whether distance elasticities vary by economic/health conditions of residents. To confirm that distance to a vaccination site indeed affects local vaccination rates, we perform a regression analysis on panel data in early 2021. Our identification strategy relies on variation in the opening dates of mass vaccination sites (*e.g.*, Disneyland), which were mostly closed by mid-2021.

### 2.1. Data

For our empirical analysis, we use the most granular population-level COVID vaccination data available: weekly vaccinations administered, by zip-code, for all of California. We merge this with location and demographic data from multiple sources. Appendix Table A1 gives summary statistics.

**Vaccination locations.** Location information including the geographic coordinates (latitude and longitude) of the 4,035 retail pharmacies in California participating in FRPP were scraped from `https://www.vaccines.gov/` as of June 2021. Locations and opening and closing dates of all mass vaccination sites were hand-assembled based on media reports and public search results (Appendix A3). Euclidean distances were computed between each vaccination site and the population centroid of each zip-code as reported by the US Department of Housing and Urban Development (2021).

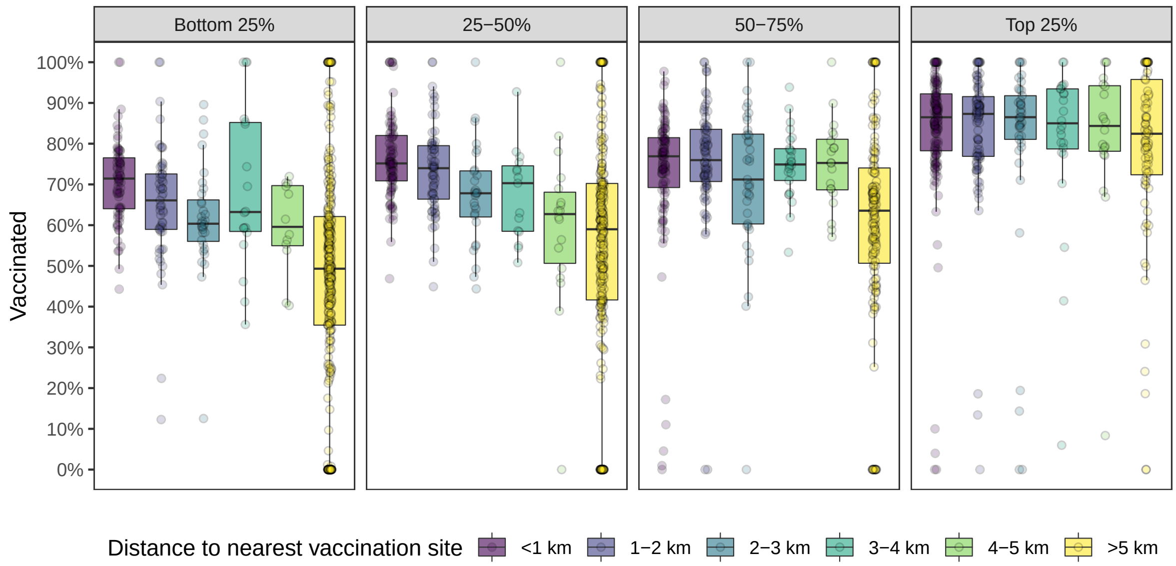
For the facility location model (Section 3), potential vaccination sites also include the three largest dollar store chains (Dollar General, Dollar Tree, and Family Dollar), which collectively operate 1,016 stores across California. Dollar store locations (latitude and longitude) were collected from ScrapeHero (2021).

**Demographics.** Demographic data were obtained from two sources. Our main demographic variable of interest, the Healthy Places Index (HPI), is a composite score that measures the well-being of a community constructed by the Public Health Alliance of Southern California (2022). Each geographic unit's HPI index is based on a weighted score across eight domains: socioeconomics, education, health care access, housing, neighborhood conditions, pollution/clean air, social factors, and transportation access (Maizlish et al. 2019). We grouped each region into HPI quartiles, where the top 25% represents the healthiest regions and the bottom 25% denotes the least healthy.

Additional demographic data were obtained from the 2019 American Community Survey (US Census Bureau 2019). Key variables include race/ethnicity, unemployment rate, poverty rate, college graduation rate, median household income, median home value, population, population density, and health insurance status.

**Vaccination rates.** Weekly COVID-19 vaccination data, by zip-code, were obtained from the California Department of Public Health (2021). Our main outcome variable is the proportion of the population over age 12 who are fully vaccinated as of March 1, 2022. In secondary analysis with panel data, we examine the proportion newly vaccinated each week from January to May 2021.

**Figure 3** **COVID vaccination rates as of March 1, 2022 by HPI quartile**




*Note.* Each circle denotes a California zip-code and the boxplot shows the distribution (25-50-75th percentiles) of vaccination rates. Euclidean distance is calculated between each zip-code population centroid and the nearest FRPP pharmacy. Each panel corresponds to a quartile of the California Healthy Places Index (HPI).

### 2.2. Empirical Specifications

In California, wide variability exists in both COVID vaccination rates and distance to the nearest vaccination site. As of June 1, 2021, for instance, full vaccination rates averaged 50% across the state's 1,764 zip-codes, with an interquartile range of 37% to 65%, a gap that persisted into mid-2022. Distance to the nearest FRPP vaccination site averaged 10.2 km, but also widely varied with an interquartile range of 1.1 km to 14.8 km, and reaching a maximum of 98.9 km.

Examining the raw data, Figure 3 highlights two key observations. First, a sizeable vaccination gap exists between residents of the most healthy (HPI top 25%, right panel) and least healthy (HPI bottom 25%, left panel) communities. Second, vaccination inequalities widen as distance to a site increases, particularly for those living in the least healthy communities (HPI bottom 25%).

Utilizing cross-sectional data on vaccination rates by zip-code, we estimate to what extent closer proximity to a retail pharmacy vaccination site correlates with higher vaccination rates. We first use a simple log-linear regression model:

$$Vaccinated_i = \beta_0 + \beta_1 LogDistance_i + \varepsilon_i \tag{1}$$

The dependent variable, $Vaccinated_i$, is the proportion of the population aged 12 and older in zip-code $i$ who are fully vaccinated as of March 1, 2022. Our main independent variable of interest, $LogDistance_i$, is the natural-log distance from the population centroid of zip-code $i$ to the nearest retail pharmacy vaccination site.

Next, we add a categorical variable for HPI quartile:

$$Vaccinated_i = \beta_0 + \beta_1 LogDistance_i + \beta_2 HPI_i + \varepsilon_i \tag{2}$$

Finally, to test whether residents of less healthy communities are more sensitive to vaccination distance, we include an interaction term between HPI and log-distance:

$$Vaccinated_i = \beta_0 + \beta_1 LogDistance_i + \beta_2 HPI_i + \beta_3 LogDistance_i \times HPI_i + \varepsilon_i \tag{3}$$

As a robustness check, we also include demographic control variables at the zip-code level. Although collinear with some of the inputs to HPI, these covariates capture the within-HPI quartile variation in demographics, health insurance status, and other factors. Full results are available in Table A2.

### 2.3. Distance-to-site and Vaccination Uptake

Table 1, regression (1) reports the unadjusted coefficient estimate of -0.069 ($p < 0.001$), suggesting that a 100% increase in distance to vaccination site corresponds to a 4.8 percentage-point decrease ($-0.069 \times ln(2) = -0.048$) in vaccination rates, across all California residents, on average. Regression (2) confirms that vaccination rates increase with HPI, even after accounting for proximity

**Table 1 Predictors of COVID vaccination rates as of March 1, 2022 per zip-code in California**

| | Dependent variable: *Fraction Fully Vaccinated* | | | | | |
|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | |
| Independent variable | Coef. | Std. error | Coef. | Std. error | Coef. | Std. error |
| Log-distance to nearest site | -0.069*** | (0.004) | -0.055*** | (0.004) | -0.016 | (0.008) |
| HPI quartile 4 (most healthy) | | | Ref. | | Ref. | |
| HPI quartile 3 | | | -0.097*** | (0.014) | -0.077*** | (0.015) |
| HPI quartile 2 | | | -0.130*** | (0.014) | -0.097*** | (0.012) |
| HPI quartile 1 (least healthy) | | | -0.193*** | (0.014) | -0.146*** | (0.014) |
| Log-distance × HPI quartile 4 | | | | | Ref. | |
| Log-distance × HPI quartile 3 | | | | | -0.039** | (0.012) |
| Log-distance × HPI quartile 2 | | | | | -0.047*** | (0.011) |
| Log-distance × HPI quartile 1 | | | | | -0.053*** | (0.010) |
| Constant | 0.755*** | (0.005) | 0.847*** | (0.010) | 0.826*** | (0.010) |
| Observations | 1,750 | | 1,750 | | 1,750 | |
| F-stat | 352.5 | | 126.8 | | 76.9 | |
| $R^2$ | 0.193 | | 0.264 | | 0.276 | |
| Adjusted $R^2$ | 0.192 | | 0.263 | | 0.273 | |

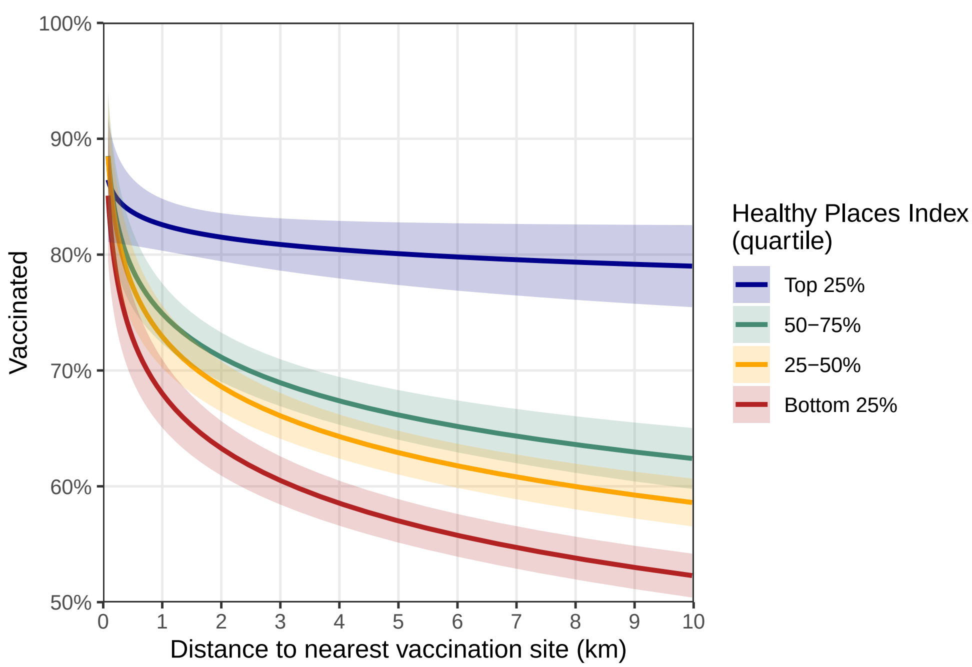
*Note.* Log-distance is calculated from each zip-code's population centroid to the nearest vaccination site at a retail pharmacy. HPI refers to the California Healthy Places Index. Robust standard errors are reported in parentheses. Significance levels: *p<0.05; **p<0.01; ***p<0.001

to a vaccination site. The interaction terms in regression (3) are statistically significant and economically meaningful: residents of less healthy communities have greater reductions in vaccination rates as distance to a site increases, as denoted by the more negative interaction coefficients for lower HPI quartiles. Doubling the distance required to get vaccinated corresponds to nearly a 5 percentage-point ($p < 0.001$) drop in vaccinations for HPI quartile 1, nearly five-fold the expected change for HPI quartile 4. Figure 4 gives adjusted vaccination rates and 95% confidence intervals, by HPI quartile and distance to the nearest site, using predicted margins under regression (3).

After controlling for key demographics including population density—a strong proxy for urban or rural locale—the interaction terms for HPI and distance remain significant ($p < 0.01$) and follow a similar pattern (Appendix Table A2). Vaccination elasticities with respect to distance are significantly steeper for lower income, less healthy populations.

The preceding evidence demonstrates a strong correlation between distance to a vaccination site and vaccination uptake. One threat to this model specification is if the set of pharmacies included in FRPP was selected in a manner that is correlated (ex ante) with both the propensity to get vaccinated and HPI—beyond the set of observable demographic variables. This seems unlikely as many participating locations were part of a national chain (*e.g.*, CVS, Walgreens), which opened store locations well in advance of the COVID vaccine gaining FDA-approval. While retail pharmacies do tend to locate in higher income, more urban communities, including additional demographic controls still upholds our main findings.

**Figure 4** **Adjusted COVID vaccination rates as of March 1, 2022 by distance to vaccination site and HPI quartile**



### 2.4. Mass Vaccination Sites

To further test whether distance to an available vaccination site *causally* affects vaccination rates, we perform a similar regression analysis using panel data on weekly vaccinations between January and May 2021. Since there is no variation in the opening dates of pharmacies participating in FRPP, we instead examine mass vaccination sites, known as super points of dispensing (PODs). Over this time period, 26 PODs began operating across California, with wide variation in locations and opening dates (Appendix Table A3). We assume the following specification:

$$NewlyVaccinated_{it} = \beta_0 + \beta_1 LogDistancePOD_{it} + \beta_2 Vaccinated_{it-1} + \alpha_i + \omega_t + \varepsilon_{it} \tag{4}$$

where $NewlyVaccinated_{it}$ is the proportion of the population aged 12 and older in zip-code $i$ who are newly vaccinated during week $t$. The variable $LogDistancePOD_{it}$ is the natural-log distance from the population centroid of zip-code $i$ to the nearest super POD that is open during week $t$. $Vaccinated_{it-1}$ is a lagged variable for the cumulative proportion of the population aged 12 and older in zip-code $i$ who are vaccinated by week $t-1$. We include this term because as the cumulative vaccination level increases over time, the remaining pool of unvaccinated individuals eligible for vaccination shrinks. We include two-way fixed effects for zip-code $i$ ($\alpha_i$) and week $t$ ($\omega_t$).

Results are given in Appendix Table A4. We again find that the proportion of residents newly vaccinated each week significantly decreases ($\beta_1 = -0.00102$, $p < 0.01$) as distance to an open POD increases. Further, as more residents of a zip-code become vaccinated, the rate of new vaccinations diminishes ($\beta_2 = -0.0471$, $p < 0.001$), as expected, due to saturation.

While we focus on the period of January to May 2021, we include week fixed effects to capture temporal changes in the wider availability of COVID vaccines, updated vaccination eligibility criteria, or changing patterns in vaccine hesitancy. We exclude observations beyond May 1, 2021 as many mass vaccination sites were closed by then once the state transitioned to more pharmacy-based vaccination provision. Of note, including geographic fixed effects controls for other potentially confounding variables such as population density, transportation access, and resident political leanings. Here, we only capture changes in vaccination rates—*within* each zip-code—as the result of a new mass vaccination site opening or closing.

Although the model performs well ($R^2 = 0.584$), this is mainly due to the two-way fixed effects. Within $R^2 = 0.027$, indicating that variation in distance to mass sites very modestly predicts vaccination rates, in accordance with evidence that most California residents ultimately received a COVID vaccination elsewhere. Together with the cross-sectional analysis for all pharmacy-based COVID vaccination sites in California, the panel data regressions provide compelling evidence demonstrating that closer proximity to a vaccination site boosts uptake.

## 3. Vaccination Location Model

Using an optimization framework, we quantify the potential gain in vaccinations achieved by substituting dollar stores with some existing retail pharmacies. Specifically, we develop a vaccination facility location model that decides which sites to operate and how to allocate capacity to different geographic regions—*i.e.*, number of vaccine doses reserved for a region—with the goal of maximizing the number of vaccinations administered under the demand model estimated in Section 2.

Let us consider $\mathcal{I}$ as the set of geographic regions (*e.g.*, census tracts or zip-codes) and $\mathcal{J}$ as the set of possible vaccination sites. We consider a fixed number of active sites $N$, each with limited vaccine supply $K$. The latter assumption can be easily relaxed. Each region includes a population of $p_i$, $\forall i \in \mathcal{I}$ residents and the distance between region $i$ and vaccination site $j$ is $d_{ij}$, $\forall i \in \mathcal{I},\ j \in \mathcal{J}$.

To obtain a reasonable assignment that captures individuals' typical preferences for visiting their local pharmacy, we assume that vaccine doses are reserved at one of the closest $M$ sites to a region. In the base case, we assume $M = 10$ but vary this in sensitivity analysis. Let $I_{ij}^M$ be an indicator that equals 1 if vaccination site $j$ is one of region $i$'s $M$ closest sites, and 0 otherwise. To add flexibility in the assignment, we allow a region's demand to be satisfied by multiple sites.

In region $i$, the demand for vaccination $V(d_{ij}, h_i)$ is defined as the fraction of the population seeking vaccination. We model demand as a function of both the distance to the assigned site $d_{ij}$ and the region's demographic characteristics $h_i$, where $h_i$ represents a multidimensional metric capturing population health, well-being, and socioeconomic status, such as HPI. As described in Section 2, we consider the estimated demand function $\hat{V}(d_{ij}, h_i)$ to be linear and decreasing in the log-distance. Lastly, we assume all vaccinations occur in a resident's home state, an assumption also imposed by Bertsimas et al. (2022).

The decision variables are:

$$z_j = \begin{cases} 1 & \text{if vaccination site } j \in \mathcal{J} \text{ is active} \\ 0 & \text{otherwise} \end{cases}$$

$$w_{ij} = \text{fraction of vaccine demand from region } i \in \mathcal{I} \text{ assigned to site } j \in \mathcal{J}$$

The vaccination facility location problem is formulated as follows:

$$(\mathcal{P}) \quad \max \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} p_i \hat{V}(d_{ij}, h_i) w_{ij} \tag{5}$$

$$\text{s.t.} \sum_{i \in \mathcal{I}} p_i \hat{V}(d_{ij}, h_i) w_{ij} \le z_j K, \quad \forall j \in \mathcal{J} \tag{5a}$$

$$\sum_{j \in \mathcal{J}} w_{ij} \le 1, \quad \forall i \in \mathcal{I} \tag{5b}$$

$$w_{ij} \le I_{ij}^M, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J} \tag{5c}$$

$$\sum_{j \in \mathcal{J}} z_j = N \tag{5d}$$

$$w_{ij} \in [0,1], \quad z_j \in \{0,1\} \tag{5e}$$

The objective function (5) maximizes aggregate vaccinations across all regions and their assigned vaccination site(s). Constraints (5a) ensure that total demand served by each vaccination site does not exceed its capacity, but we permit multiple vaccination sites to serve each region. Constraints (5b) ensure that no more than a 100% of vaccine demand is assigned. Constraints (5c) ensure that vaccines are reserved for vaccine-seeking residents within each region's $M$ closest sites. Finally, constraint (5d) imposes a total budget of $N$ active vaccination sites in the state. This results in a mixed-integer program, where $w_{ij}$ is a continuous variable between 0 and 1 and $z_j$ is a binary decision variable. This is essentially a variation of the maximal covering location problem (MCLP) with an estimated heterogeneous coverage function (Church and ReVelle 1974). We discuss additional assumptions in Appendix B.

## 4. Results

We employ the estimated demand function in Table 1 column (3), such that vaccination uptake depends on distance to the assigned site and HPI quartile. We compare two strategies: "Pharmacy-only", which utilizes only the pharmacies participating in FRPP, and "Pharmacy + Dollar", which considers a greater set of feasible sites including FRPP pharmacies and dollar stores. The total number of selected sites ($N = 4,035$) and per-store capacity remain constant under both strategies. Table 2 gives the number of predicted vaccinations under each strategy and by HPI quartile.

Under the Pharmacy-only strategy, we obtain a predicted vaccination rate slightly below the 70% maximum due to our assumption that residents can only be assigned to one of their tenth-closest locations, which leads to excess capacity at some sites. Under this solution, average vaccination rates vary widely by HPI, with a 16 percentage-point difference between the top and bottom HPI quartiles. This difference occurs for two reasons. First, residents of the top HPI quartile tend to live closer to existing pharmacy sites. Second, these residents are less sensitive to long distances

**Table 2 Total number of vaccinations under Pharmacy-only and Pharmacy + Dollar strategies**

| | Vaccinations in millions (% of population) | | | | |
|---|---|---|---|---|---|
| | | HPI quartile | | | |
| Strategy | All | Bottom 25% | 25-50% | 50-75% | Top 25% |
| All residents | | | | | |
| Pharmacy-only | 24.2 (66%) | 5.33 (58%) | 6.10 (65%) | 6.29 (67%) | 6.48 (74%) |
| Pharmacy + Dollar | 25.7 (70%) | 5.86 (64%) | 6.47 (69%) | 6.58 (70%) | 6.79 (77%) |
| Walking distance (<1 km) | | | | | |
| Pharmacy-only | 5.70 (16%) | 1.49 (16%) | 1.65 (18%) | 1.61 (17%) | 0.95 (11%) |
| Pharmacy + Dollar | 7.13 (19%) | 2.25 (25%) | 2.15 (23%) | 1.85 (20%) | 0.87 (10%) |

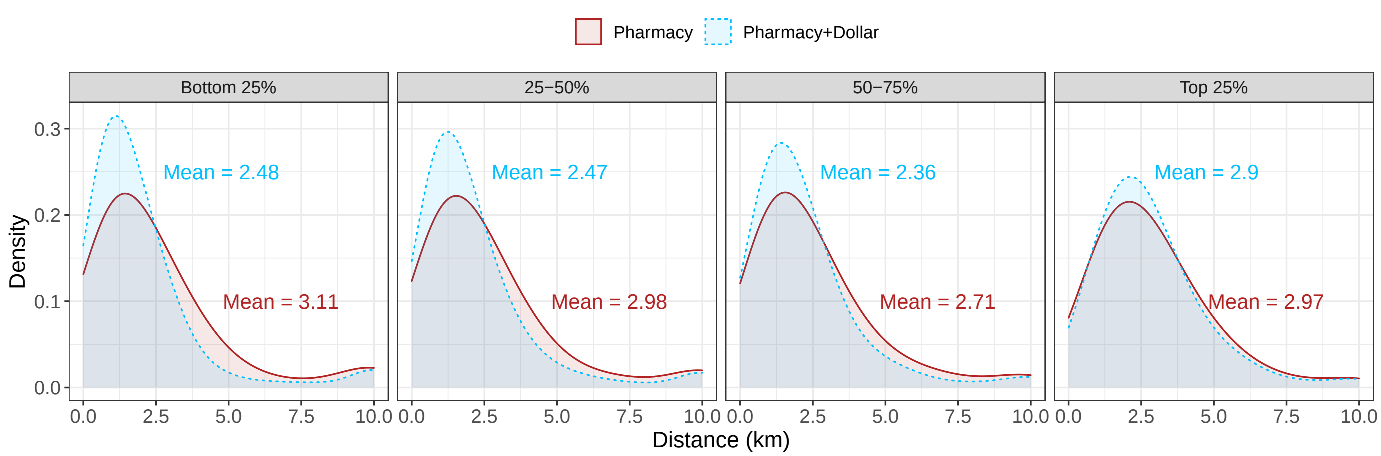
*Note.* Walking distance refers to census tracts assigned to a vaccination site within 1 km of the tract's population centroid. Number of closest feasible sites $M = 10$, and maximum achievable vaccination rate $\gamma = 70\%$.

and are thus willing to travel farther to be vaccinated. Figure 5 shows the distance distribution by HPI quartile. Under the Pharmacy-only *optimal* assignment, residents in the bottom HPI quartile encounter 4% longer distance requirements, on average, relative to the top quartile. Although this difference may seem modest, residents in the bottom quartile are not only less likely to be vaccinated overall, they also face the steepest vaccination distance-elasticity (Figure 4).

Adding dollar stores as alternative access points can partially alleviate these inequalities. The Pharmacy + Dollar strategy replaces 744 (out of 4,035) FRPP pharmacies with dollar stores, which collectively fulfill demand for 4.73 million residents, 18% of all vaccinations. Dollar stores' propensity to locate in more disadvantaged areas (see Figure 2) makes them particularly well-positioned to increase vaccinations in vulnerable areas—the exact locations with low uptake (see Figure 3). Adding dollar stores as part of a vaccine delivery strategy shortens the average distance to a site by 20% (bottom HPI quartile), 17% (second HPI quartile), 13% (third HPI quartile), and 2% (top HPI quartile). This shift could theoretically result in 1.5 million additional vaccinations across California, of which 35% accrue to the bottom HPI quartile (Table 2). Of note, although some geographic areas might be forced to travel farther under this strategy, the average distance to a site—and the number of people vaccinated—improves across all four HPI quartiles. This suggests that this policy improves overall efficiency of the vaccination site assignment problem rather than just shift resources from high-HPI regions to low-HPI communities.

In addition to improvements in the *average* distance to a vaccination site, the right tail of the distribution shrinks (Figure 5), implying that dollar stores also offer closer vaccination access for the most pharmacy-isolated communities. The Pharmacy + Dollar strategy allows an additional 1.4 million people, a 25% increase, to be within walking distance ($< 1$ km) of a vaccination site. More than half of these predicted vaccinated individuals reside in low HPI areas and are thus less likely to have transportation access.

**Figure 5** **Density of distance to site by census tract under the Pharmacy-only and Pharmacy + Dollar strategies**



At the county-level, more rural and less populated counties see a larger drop in average distance to the assigned site, with most counties experiencing an rise in vaccination rates when dollar stores replace some FRPP pharmacies (Figure C1). The greatest predicted gains occur in Los Angeles (+8% or 484,531 more vaccinations), Santa Clara (+17% or 164,551 more vaccinations), San Diego (+7% or 151,440 more vaccinations), Alameda (+17% or 132,236 more vaccinations), and Contra Costa (+16% or 103,423 more vaccinations) (Figure C2). The additional vaccinations are due to increased capacity within the county, a better choice of locations, or a combination of both.

LA County sees a sizeable increase in vaccination sites selected under the Pharmacy + Dollar strategy: all 992 pharmacy sites remain active and 147 dollar stores are added. A map (Figure C3) shows the optimal set of dollar stores locating near low HPI areas in the San Fernando Valley, South Los Angeles, and San Gabriel Valley. A recent study by Wisseh et al. (2021) reports that one-quarter of census tracts in LA County are in *pharmacy deserts*—neighborhoods with no pharmacies within one mile in urban areas or ten miles in rural areas. In contrast to rural pharmacy deserts, many of these LA communities are densely populated, predominantly by Black and Hispanic residents, and frequently characterized by poverty, high crime, and fewer medical professionals serving the area. Pharmacy deserts often overlap with low HPI tracts, making dollar stores a viable option to fill the pharmacy void in these underserved communities and help close the vaccination gap (Katje 2021). San Diego also sees significant gains in predicted vaccinations under this policy, with most of the 53 optimally selected dollar stores locating in the bottom two HPI quartiles (Figure C4).

For some counties, better locating vaccination sites is more important than increasing the number of vaccination access points. For example, Kern County, home to more than 800,000 Californians, obtains 1.3% *more* predicted vaccinations despite operating with 33 *fewer* vaccination sites (30 new dollar stores but 63 fewer FRPP pharmacies). Another example is San Bernardino County, which replaces 76 FRPP pharmacies with 55 dollar stores, a net decrease of 21 sites, but reports virtually no change in vaccination numbers. Riverside County reports similar behavior with 102 fewer FRPP pharmacies but 51 additional dollar stores (Figure C5).

Although predicted vaccinations increase in aggregate under the Pharmacy + Dollar strategy, some counties nevertheless would see slightly fewer vaccinations under this policy (Figure C2). Orange County, the most negatively impacted county, would operate 34 new dollar stores but lose 69 FRPP pharmacies. Such consolidation would increase the average distance to a vaccination site from 1.4 km to 1.7 km, resulting in approximately 24,000 (1%) fewer vaccinations across the county. The optimally selected dollar stores, however, are concentrated in low HPI areas, improving proximity to a vaccination site for more vulnerable residents (Figure C6). We note that most tracts in Orange County belong to the top HPI quartiles. Based on our estimated distance elasticities, high HPI residents are less sensitive to distance, and thus, in reality, they may be more willing to travel farther to get vaccinated. Our model, however, does not permit such heterogeneous behavior, as we limit the assignment to the $M$ closest vaccination sites for all geographic regions. If this assumption is relaxed, vaccination numbers climb back up, as expected.

We explore additional sensitivity analysis in Appendix D. Our qualitative findings hold if per-store capacity and the number of feasible locations varies. Of note, when vaccination distance elasticities are assumed to be homogeneous across HPI quartiles (*i.e.*, using regression model (1) instead of (3)), the optimal solution shifts resources from lower HPI regions to higher HPI areas, further widening the vaccination gap. This highlights the importance of accounting for social and economic factors in the distribution and delivery of vaccines to ensure equity in access and increase uptake in the most vulnerable communities.

### 4.1. Limitations and Future Work

Our study has several limitations. The demand estimation relies on zip-code level vaccination data in California, given the lack of more granular vaccination data in the state. Ideally, a full nationwide analysis would better estimate the causal effect of vaccination access (*e.g.*, distance to a site) on uptake and how it might vary by state, which could highlight new insights and policy implications. We use distance to the nearest FRPP pharmacy as a proxy for vaccine *access*; in reality, people may be vaccinated at a site farther from home, or a non-FRPP location (*e.g.*, physician's office).

Our facility location model is implemented at the census tract-level and uses Euclidean distances between population-weighted centroids and vaccination sites to approximate travel distance, but this ignores within-tract spatial heterogeneity. We maximize the total number of vaccinations and ignore other objectives (*e.g.*, COVID-related deaths, operating costs, etc.) that are likely important to decision-makers during a pandemic. Follow-up work could extend our model to a multi-period setting to study, for example, vaccination roll-out campaigns—where sites are opened sequentially instead of simultaneously—and dynamic inventory allocation policies based on each region's time-varying epidemic conditions and number of susceptible individuals. These extensions, along with scheduling of healthcare staff in dollar stores and routing decisions, would be of practical use given the current shortage of healthcare workers and resources needed for the widespread delivery of booster doses.

## 5. Discussion and Policy Implications

As COVID-19 evolves into endemic status—when viral transmission persists but is less disruptive to daily activities—we will continue to rely on periodic vaccine boosters to mitigate future waves, especially for high-risk populations (*e.g.*, the elderly and those with a weakened immune system). Worldwide COVID-19 vaccination efforts have highlighted the critical need for a multi-faceted approach that combines speed of deployment (*e.g.*, through expedited vaccine approval, manufacturing, and distribution), scalability (*e.g.*, via mass vaccination centers), and customization (*e.g.*, using mobile and pop-up vaccination clinics). Vaccination uptake depends not only on having adequate supply, but on socioeconomic factors, vaccine information and education, hesitancy, as well as accessibility of vaccination sites (Crane et al. 2021).

In this work, we estimate the link between proximity to a vaccination site and uptake and find that longer distances indeed result in lower vaccination rates. Moreover, distance does not equally affect all socioeconomic groups, suggesting that communities that are more sensitive to distance (*e.g.*, regions with a low HPI index in California) should be prioritized and approached differently to achieve similar outcomes. Targeted initiatives could entail, for example, reserving capacity at certain sites for residents of nearby neighborhoods, apportioning more capacity to strategically located sites or simply opening more sites in vulnerable places (*e.g.*, areas with limited access to automobiles or public transit). Offering last-mile transportation in isolated areas with no pharmacies, nor dollar stores, could help close the sizeable vaccination gap attributable to inaccessible vaccination locations.

The federal government's partnership with retail pharmacies, FRPP, aimed to make COVID vaccines widely available to all, yet the existing locations of participating pharmacies may have unwittingly exacerbated vaccination inequalities (Attonito et al. 2021). Moreover, ethnic and racial disparities also exist. As of April 2022, more than 60% of Asians and 54% of Whites in the U.S. had received a booster, compared to 44% of Blacks and 40% of Hispanics (Ndugga et al. 2022). Pharmacy deserts are disproportionately located within Black and Hispanic neighborhoods in the most populous U.S. cities (Guadamuz et al. 2021), further limiting access to life-saving medications, diagnostic testing, and immunizations.

We propose a complementary strategy to FRPP: offer vaccinations at *optimally* selected dollar stores. Adding Dollar General stores only to FRPP will bring vaccines closer to most individuals, surpassing the Biden administration's goal of having 90% of the population within 5 miles of a vaccination center (Chevalier et al. 2022). Our analysis shows that, in California, FRPP increases systemic disparities in terms of proximity and supply access, and that incorporating dollar stores into the program could alleviate these undesirable, yet unavoidable, consequences of the program. We expect similar outcomes in other jurisdictions, particularly those that are racially and economically segregated, and currently face wide gaps in vaccination rates. The benefits of including dollar stores as candidate vaccination locations are twofold: (1) they reallocate vaccine supply from areas with excess capacity (due to the higher concentration of retail pharmacies in high-income areas) to areas with scarce supply, and (2) they bring supply closer to the populations who are less likely to seek vaccination when faced with longer distances.

To test feasibility and community acceptance, a dollar store vaccination campaign could be initially implemented in counties most likely to benefit from the addition of discount retailers. In California, the top three counties to potentially benefit are Los Angeles, Santa Clara, and Alameda (see Table A5 for top 10 list of counties). These counties lack supply in more vulnerable and isolated areas due to the sub-optimal location of retail pharmacies. Operationally, one could imagine using a rotating program where medical professionals travel between stores within a specific geography to offer inoculation during specific days/times in each week. As some of these discount chains are presently moving into the pharmacy business themselves (Katje 2021), we expect them to enhance their healthcare capabilities and eventually have, at least in some locations, their own pharmacy services team on site.

Our study illustrates one potential solution to address inequalities in access to COVID-19 vaccines. Policymakers could consider other retail chains that share characteristics with dollar stores (*e.g.*, gas stations, post offices, etc.). Such a partnership could also assist in other emergency settings, such as distributing COVID test kits, emergency medical supplies, and personal protective equipment. By shedding light on understanding the role of vaccine access in population-level health outcomes, our work offers a simple quantitative framework that could assist with mitigation strategies against a seasonal outbreak or an endemic disease—a likely outcome for COVID.

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## Appendix A: Supplementary Tables

**Table A1 California summary statistics**

| | Mean | SD |
|---|---|---|
| Number of retail pharmacy vaccination sites | 4,110 | - |
| Number of dollar stores | 1,016 | - |
| State population | 37,253,956 | - |
| Number of zip-codes | 1,764 | - |
| Population (per zip-code) | 22,265 | 22,608 |
| Population density (residents per sq mi) | 3,425 | 5,574 |
| Race/ethnicity | | |
| % White | 0.51 | 0.28 |
| % Black | 0.04 | 0.07 |
| % Asian | 0.09 | 0.13 |
| % Hispanic | 0.30 | 0.25 |
| % Other | 0.05 | 0.07 |
| Health insurance | | |
| % Employer | 0.41 | 0.17 |
| % Medicare | 0.15 | 0.11 |
| % Medicaid | 0.20 | 0.15 |
| % Other | 0.15 | 0.09 |
| College graduation rate | 0.31 | 0.21 |
| Unemployment rate | 0.07 | 0.06 |
| Poverty level | 0.10 | 0.11 |
| Median household income ($000s) | 70.2 | 40.1 |
| Median home value ($000s) | 501.1 | 398.3 |
| HPI (contiuous value in $[0,1]$) | 0.47 | 0.29 |
| Distance to nearest vaccination site (km) | | |
| HPI quartile 4 (most healthy) | 3.8 | 5.7 |
| HPI quartile 3 | 8.1 | 13.3 |
| HPI quartile 2 | 12.0 | 13.5 |
| HPI quartile 1 (least healthy) | 15.3 | 16.2 |

*Note.* Census demographics are at the zip-code level and include race/ethnicity, health insurance, college graduation rate, unemployment rate, poverty level, median household income, median home value, population density, and population.

**Table A2 Predictors (including demographic controls) of vaccination rates as of March 1, 2022 at the zip-code level in California**

| | Dependent variable: *Fraction Fully Vaccinated* | |
|---|---|---|
| Independent variable | Coef. | Std. error |
| Log-distance to nearest site | -0.0026 | (0.0094) |
| HPI quartile 4 (most healthy) | Ref. | |
| HPI quartile 3 | 0.013 | (0.018) |
| HPI quartile 2 | 0.0050 | (0.023) |
| HPI quartile 1 (least healthy) | -0.037 | (0.031) |
| Log-distance × HPI quartile 4 | Ref. | |
| Log-distance × HPI quartile 3 | -0.025* | (0.012) |
| Log-distance × HPI quartile 2 | -0.030** | (0.011) |
| Log-distance × HPI quartile 1 | -0.033** | (0.010) |
| Race White | Ref. | |
| Race Black | -0.019 | (0.077) |
| Race Asian | 0.255*** | (0.038) |
| Race Hispanic | 0.221*** | (0.041) |
| Race Other | -0.096 | (0.114) |
| Health insurance employer | -0.014 | (0.099) |
| Health insurance Medicare | 0.163 | (0.115) |
| Health insurance Medicaid | 0.143 | (0.113) |
| Health insurance other | -0.281* | (0.116) |
| College graduation rate | 0.316*** | (0.073) |
| Unemployment rate | -0.391* | (0.159) |
| Poverty level | 0.049 | (0.109) |
| Median household income ($000s) | 0.00027 | (0.00036) |
| Median home value ($000s) | 0.00011*** | (0.000032) |
| Population density | -3.4e-06*** | (9.9e-07) |
| Population | 1.8e-07 | (2.1e-07) |
| Constant | 0.474*** | (0.084) |
| Observations | 1,750 | |
| F-stat | 51.2 | |
| $R^2$ | 0.408 | |
| Adjusted $R^2$ | 0.401 | |

*Note.* Log-distance is calculated from each zip-code's population centroid to the nearest vaccination site at a retail pharmacy. HPI refers to the California Healthy Places Index. Robust standard errors are reported in parentheses. Significance levels: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

**Table A3 Opening and closing dates of super points of dispensing (PODs) in California**

| Location | Latitude | Longitude | Opened | Closed |
|---|---|---|---|---|
| Petco Park | 32.707 | -117.157 | 1/11/2021 | 3/20/2021 |
| San Mateo Event Center | 37.547 | -122.302 | 1/11/2021 | 5/26/2021 |
| Disneyland Resort | 33.812 | -117.922 | 1/13/2021 | 4/30/2021 |
| Dodger Stadium | 34.074 | -118.240 | 1/15/2021 | 5/31/2021 |
| Long Beach Convention Center | 33.765 | -118.189 | 1/16/2021 | 7/30/2021 |
| Six Flags Magic Mountain Valencia | 34.426 | -118.597 | 1/19/2021 | 4/18/2021 |
| Cal State Northridge | 34.241 | -118.528 | 1/19/2021 | 6/7/2021 |
| Forum Inglewood | 33.958 | -118.342 | 1/19/2021 | 6/13/2021 |
| Pomona Fairplex | 34.082 | -117.765 | 1/19/2021 | 6/13/2021 |
| LA County Office of Education | 33.917 | -118.129 | 1/19/2021 | 6/13/2021 |
| Cal Expo | 38.590 | -121.422 | 1/21/2021 | 9/30/2021 |
| City College of San Francisco | 37.725 | -122.453 | 1/22/2021 | 6/26/2021 |
| Soka University | 33.557 | -117.734 | 1/23/2021 | 6/5/2021 |
| Cal State San Marcos | 33.130 | -117.160 | 1/31/2021 | 4/11/2021 |
| Cal Poly Pomona | 34.058 | -117.822 | 2/5/2021 | 5/18/2021 |
| Levis Stadium | 37.403 | -121.970 | 2/8/2021 | 6/24/2021 |
| Del Mar Fairgrounds | 32.974 | -117.257 | 2/12/2021 | 4/13/2021 |
| Cal State Los Angeles | 34.067 | -118.168 | 2/16/2021 | 4/11/2021 |
| Oakland Coliseum | 37.752 | -122.201 | 2/16/2021 | 5/23/2021 |
| Alameda Fairgrounds | 37.660 | -121.897 | 2/17/2021 | 6/1/2021 |
| Anaheim Convention Center | 33.801 | -117.921 | 2/23/2021 | 6/5/2021 |
| Santa Ana College | 33.758 | -117.889 | 2/24/2021 | 6/5/2021 |
| San Francisco Moscone Center | 37.784 | -122.401 | 2/25/2021 | 5/28/2021 |
| Stockton Arena | 37.956 | -121.296 | 3/30/2021 | 4/30/2021 |
| Orange County Fair Event Center | 33.666 | -117.903 | 3/31/2021 | 6/5/2021 |
| Cal State Bakersfield | 35.349 | -119.103 | 4/1/2021 | 5/14/2021 |

**Table A4 Vaccination regressions with panel data from January 12 to May 1, 2021**

| Independent variable | Dependent variable: *% Vaccinated in Week t* |
|---|---|
| Log-distance to Nearest Open POD | -0.00102** |
| | (0.00038) |
| % Vaccinated by Week $t-1$ | -0.0471*** |
| | (0.0060) |
| Fixed effects | Zip, Week |
| Observations | 25,845 |
| F-stat | 33.64 |
| $R^2$ | 0.584 |
| Adjusted $R^2$ | 0.554 |
| Within $R^2$ | 0.027 |

*Note.* Observations are at the zip-code-week level, between January 12 and May 1, 2021. Super points of dispensing (PODs) refer to mass vaccination sites, such as Disneyland. Log-distance is calculated from each zip-code's population centroid to the nearest open POD. Standard errors are clustered at the zip-code level and reported in parentheses. Significance levels: $^{*}$p<0.05; $^{**}$p<0.01; $^{***}$p<0.001

**Table A5 Locations of 50 dollar stores to open in California (assuming all retail pharmacies remain active)**

| | Number of dollar stores | | | | |
|---|---|---|---|---|---|
| | | HPI quartile | | | |
| County | All | Bottom 25% | 25-50% | 50-75% | Top 25% |
| Los Angeles | 25 | 18 | 5 | 2 | 0 |
| Santa Clara | 8 | 0 | 0 | 2 | 6 |
| Alameda | 7 | 0 | 1 | 5 | 1 |
| Contra Costa | 3 | 0 | 3 | 0 | 0 |
| Sacramento | 2 | 1 | 0 | 1 | 0 |
| San Diego | 2 | 2 | 0 | 0 | 0 |
| Marin | 1 | 0 | 0 | 0 | 1 |
| San Mateo | 1 | 0 | 0 | 0 | 1 |
| Solano | 1 | 0 | 1 | 0 | 0 |
| **Total** | **50** | **21** | **10** | **10** | **9** |
| $\Delta$ Vaccinations (million) | +0.32 | +0.13 | +0.09 | -0.01 | +0.11 |

*Note.* We modify the budget constraint (5d) in our optimization model to select all current retail pharmacies, and 50 additional dollar stores. The model optimally selects the 50 dollar store locations (including 21 stores within census tracts in the bottom HPI quartile), resulting in 0.32 million additional vaccinations in California (including 0.13 million in the bottom HPI quartile).

## Appendix B: Model Assumptions

For the empirical demand estimation, we utilize vaccination rates at the zip-code level in California, which are the most granular data available. There are 1,764 zip-codes in California (average population: 22,265). For the facility location optimization model, we assign each of the 8,057 census tracts in California (average population: 4,624) to one or more vaccination sites. We compute the Euclidean distance from the population centroid of each tract to every candidate vaccination location. This effectively assumes that all residents in a tract share the same travel distance to any given site, a reasonable assumption because census tracts are generally geographically small (*i.e.*, 75% of census tracts are less than 1.8 square-miles in area). Although we use zip-code data in the empirical analysis (tract-level vaccination data do not exist), switching to tracts for the optimization model allows for a finer spatial allocation across vaccination sites. Our main demographic variable of interest, HPI, is highly spatially correlated given that many of its inputs (*e.g.*, clean air, housing, transportation access) are themselves spatially correlated. Thus, we would expect the data generating process that maps distance to a vaccination site and vaccination uptake to be similar at the zip-code and tract levels.

The capacity $K$ of a single vaccination site is assumed to be:

$$K = \frac{\gamma \sum_{\forall i} p_i}{N}$$

where $\gamma \in [0,1]$ is a constant representing the state vaccination rate, and $p_i$ is the population of region $i$. Thus, the numerator is the total number of people vaccinated by a certain date. One can think of $K$ as the implicit per-store capacity needed to cover all vaccinated residents, given the set of current vaccination sites, $N$. In the baseline model we set $\gamma = 70\%$, the California vaccination rate as of March 1, 2022, and perform sensitivity analysis with respect to it. Although in practice, vaccinations occur over multiple periods, our model focuses on the single decision of where to offer vaccinations. Over time, as periodic booster vaccinations become routine, we can think of $K$ as the steady-state per-store capacity required to serve the local community.

In June 2021, California operated $N = 4,035$ retail pharmacy COVID vaccination sites, and had an additional 1,016 dollar stores, serving as potential vaccination sites. The optimization model constrains the selected number of vaccination sites to $N$. Although this assumption is not critical, holding constant the total number of stores allows us to select the optimal mix of existing locations and potential dollar stores while maintaining the same store-level capacity and number of vaccine access points across the state.

We assume that residents are vaccinated at their assigned site, which is not necessarily the closest location. However, we assume that residents can only be vaccinated at one of the $M$ sites closest to their home tract, to maintain a more realistic vaccination site choice. We set $M = 10$ in the baseline scenario—90% of the resulting feasible sites for each tract are within 10km—but we vary $M \in \{5,\ 20\}$ in sensitivity analysis in Appendix D.

Lastly, we ignore heterogeneity in efficacy or vaccine type and eligibility across different manufacturers. These simplifying assumptions help ensure that we obtain a feasible solution and nevertheless provide key managerial insights on deploying a more efficient and equitable vaccination delivery strategy.

## Appendix C: Supplementary Figures

**Figure C1** **Mean distance to assigned site and predicted vaccination rates, by county, under Pharmacy-only (circle) vs. Pharmacy + Dollar Store (diamond) strategies**

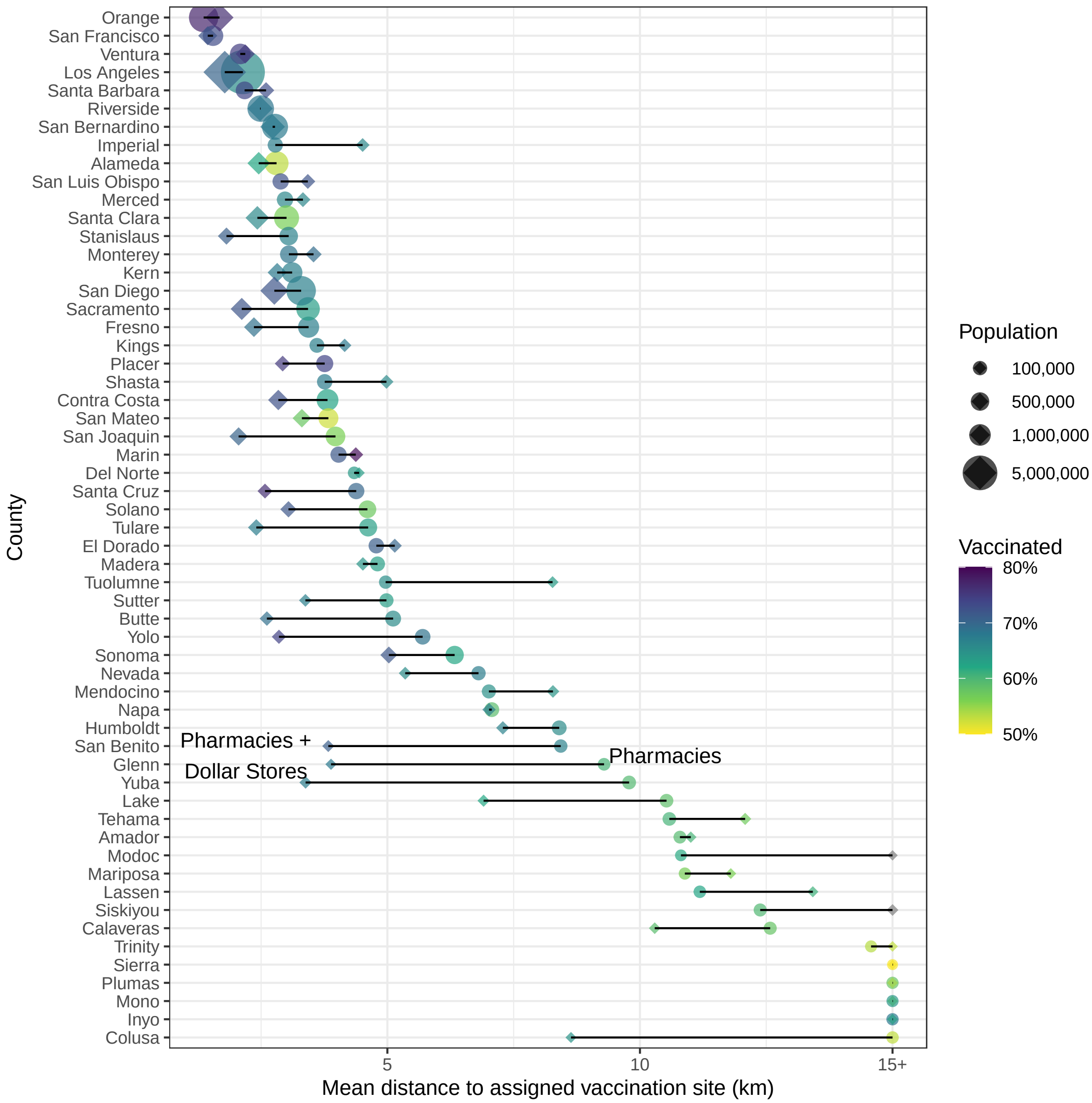
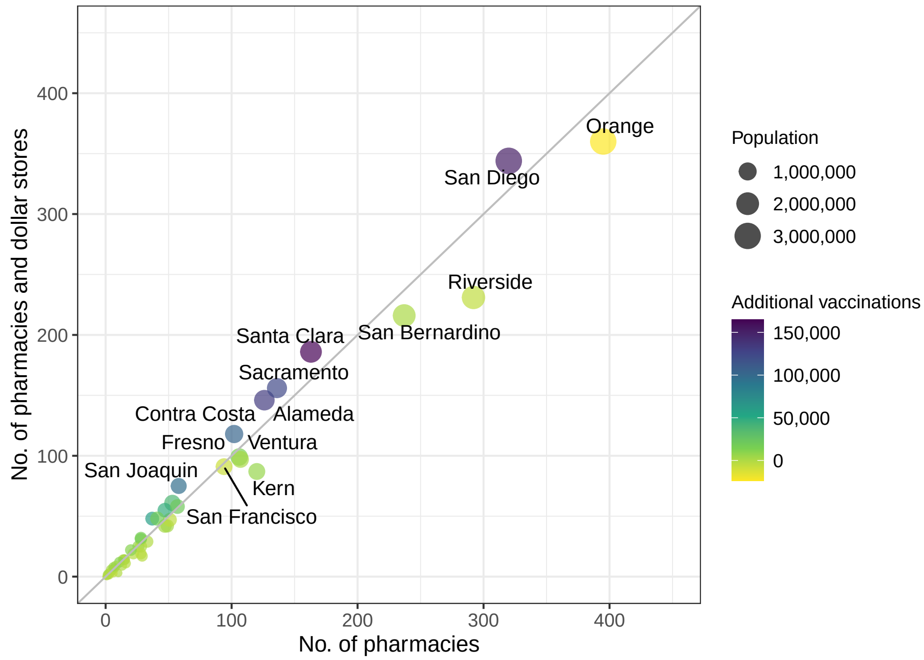


**Figure C2** **Optimal number of stores under Pharmacy-only (x-axis) vs. Pharmacy + Dollar Store (y-axis) strategies**




*Note.* Los Angeles County: 902 pharmacies and 1,069 pharmacies + dollar stores (484,531 additional vaccinations).

**Figure C3** **Optimal dollar store locations - Los Angeles County**

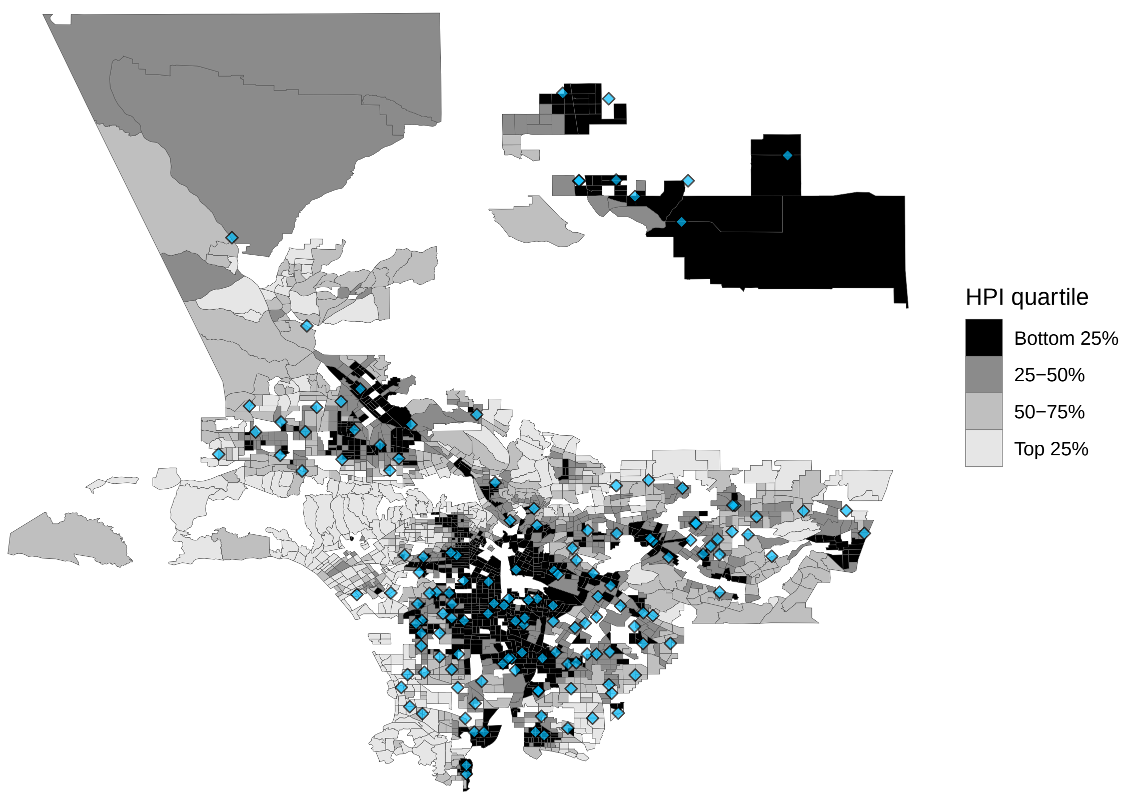


**Figure C4** **Optimal dollar store locations - San Diego County**

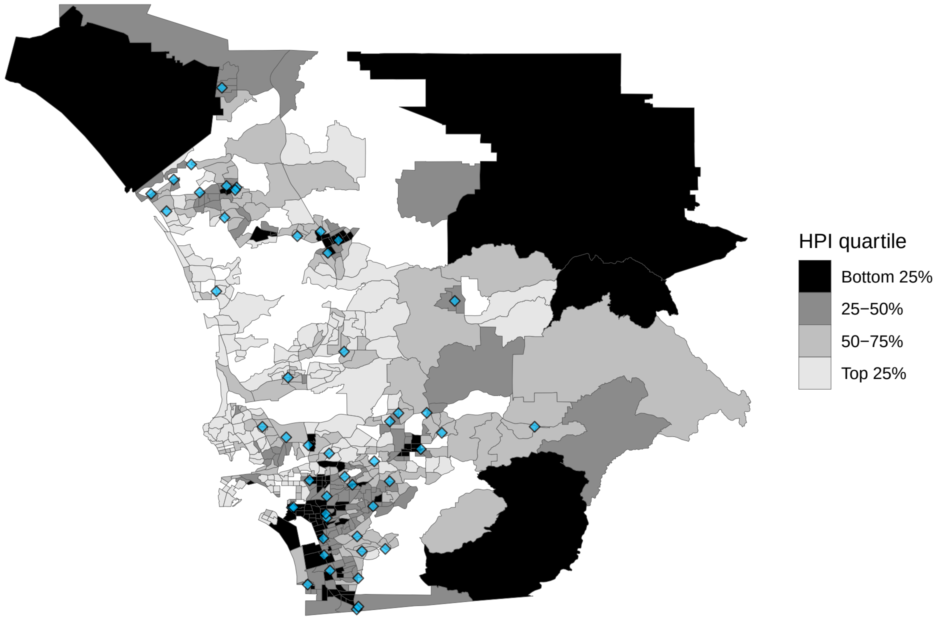
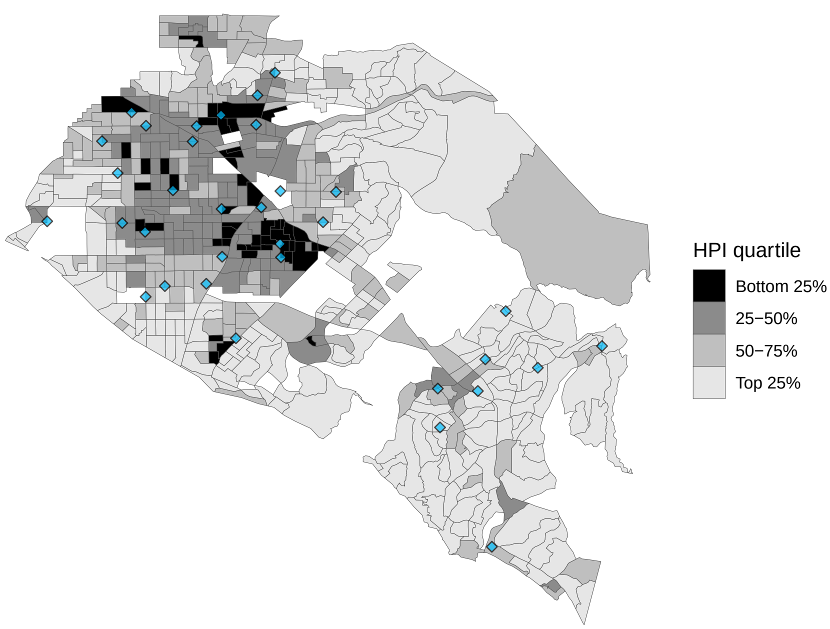



**Figure C5** **Optimal dollar store locations - Riverside County**


**Figure C6** **Optimal dollar store locations - Orange County**



## Appendix D: Sensitivity Analysis

We analyze the sensitivity of our optimization results with respect to various assumptions. We vary the capacity $\gamma$ of each vaccination site, the number of permissible vaccination locations $M$ for a single region, and the estimated demand function $\hat{V}$. The resulting vaccinations and average distances per HPI quartile are reported in Table D6.

### D.1. Per-store Capacity

We consider a 20% increase in per-store vaccination capacity ($\gamma = 0.84$), to allow for more flexibility in where residents are vaccinated. This could also be thought of as a temporal buffer in administering vaccinations, since residents are typically vaccinated in different time periods. Under the Pharmacy-only scenario, 20% higher store capacity leads to nearly 2 million (8%) additional vaccinations because the average distance to a vaccination site drops from 2.9 km to 2.3 km, as more residents can be assigned to a closer vaccination site. The largest gains accrue to those in the lowest HPI, with 550,000 additional predicted vaccinations, a 10% increase.

Under the Pharmacy + Dollar strategy, vaccination rates are higher than with the Pharmacy-only strategy, assuming a baseline capacity $\gamma = 0.70$; increasing $\gamma$ by 20% generates 5% more vaccinations when dollar stores are included in the feasible set. Once again, residents in the bottom 25% of HPI benefit the most with the greatest (35%) reduction in distance to a vaccination site. This occurs largely because the marginal dollar store opened is closer to the lowest HPI quartile, so increasing store capacity further benefits these individuals.

### D.2. Closest Feasible Locations

Next, we vary the set of closest vaccination sites $M \in \{5, 10, 20\}$ to cover each tract. Allowing a greater set of candidate locations increases model flexibility, but comes at the cost of requiring some people to travel farther to be vaccinated. Under larger values of $M$, residents can access more vaccine supply—but at a greater distance—two counterbalancing effects in determining vaccination uptake.

Increasing $M$ under the Pharmacy-only strategy, we observe that the top HPI quartile witnesses a sizeable increase in distance to a vaccination site (from 3.0 km to 4.3 km, on average, in the base case), but vaccination rates are only modestly affected since these communities are less sensitive to distance compared to lower HPI regions. In some sense, the facility location model protects lower HPI regions from assigning them to excessively far-away vaccination sites because their vaccination demand elasticity is significantly steeper, even with small increases in distance. We observe qualitatively similar results under the Pharmacy + Dollar strategy: increasing the set of feasible stores shifts more of the burden to higher HPI regions, as expected.

While we assume a homogeneous $M$ for all HPI quartiles, in practice residents of high HPI regions may consider a greater set of sites (larger $M$) when seeking vaccination (*e.g.*, due to better transportation access), which could potentially lead to even higher vaccination uptake than currently predicted by the model.

We note that dollar stores appear more beneficial when residents have limited options for vaccination, or face limited vaccine supply (*i.e.*, when $M$ and $\gamma$ are small). In these settings, dollar stores offer considerable benefit for lower HPI quartiles, the exact communities facing extra vaccination hurdles due to, for example, limited transportation options, inflexible work or childcare schedules, or living within a pharmacy desert.

### D.3. Demand Function

In our earlier analysis, we use the estimated vaccination demand function $\hat{V}$ using regression model (3), which explicitly captures differential vaccination distance elasticities by HPI quartile (Table 1). Here, we instead assume a single demand function, regardless of HPI, using regression model (1).

Ignoring the heterogeneous sensitivity to distance results in a wider vaccination gap between the top and bottom HPI quartiles. Holding constant our other parameter assumptions ($\gamma = 0.7$, $M = 10$), the Pharmacy + Dollar strategy generates a 3% *increase* in vaccinations among the top HPI quartile, while the bottom HPI quartile sees a 2% *decrease* in vaccinations, relative to the predicted levels under regression (3) (Table 5). The top HPI quartile (bottom HPI quartile) experiences a commensurate decrease (increase) in distance to an assigned vaccination site. The demand function from model (1) favors higher HPI quartiles as they tend to live closer to pharmacy vaccination sites, while the demand function from model (3) strategically selects more sites in lower HPI quartiles.

**Table D6 Total number of vaccinations and average distance to site for each HPI quartile**

| | | | Vaccinations (million) | | | | | Average distance (km) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | HPI quartile | | | | | HPI quartile | | | |
| Strategy | M | $\gamma$ | All | Bottom 25% | 25-50% | 50-75% | Top 25% | All | Bottom 25% | 25-50% | 50-75% | Top 25% |
| **Demand function from regression model (3)** | | | | | | | | | | | | |
| Pharmacy-only | 5 | 0.7 | 23.66 | 5.03 | 5.99 | 6.21 | 6.44 | 2.37 | 2.75 | 2.54 | 2.17 | 2.13 |
| | 10 | 0.7 | 24.20 | 5.33 | 6.10 | 6.29 | 6.48 | 2.94 | 3.12 | 2.98 | 2.71 | 2.97 |
| | 20 | 0.7 | 24.46 | 5.55 | 6.13 | 6.28 | 6.50 | 3.91 | 3.73 | 3.79 | 3.81 | 4.29 |
| | 5 | 0.84 | 25.68 | 5.64 | 6.47 | 6.66 | 6.92 | 2.09 | 2.36 | 2.22 | 1.85 | 1.95 |
| | 10 | 0.84 | 26.16 | 5.88 | 6.57 | 6.73 | 6.98 | 2.30 | 2.52 | 2.30 | 1.99 | 2.40 |
| | 20 | 0.84 | 26.38 | 5.98 | 6.61 | 6.76 | 7.03 | 2.59 | 2.47 | 2.33 | 2.29 | 3.20 |
| Pharmacy + Dollar | 5 | 0.7 | 25.59 | 5.73 | 6.51 | 6.62 | 6.73 | 1.93 | 1.99 | 1.93 | 1.82 | 1.98 |
| | 10 | 0.7 | 25.70 | 5.86 | 6.47 | 6.58 | 6.79 | 2.56 | 2.48 | 2.47 | 2.36 | 2.90 |
| | 20 | 0.7 | 25.72 | 5.98 | 6.53 | 6.61 | 6.60 | 2.95 | 2.68 | 2.53 | 2.69 | 3.86 |
| | 5 | 0.84 | 26.87 | 6.11 | 6.75 | 6.88 | 7.13 | 1.63 | 1.61 | 1.61 | 1.55 | 1.74 |
| | 10 | 0.84 | 27.08 | 6.20 | 6.77 | 6.92 | 7.19 | 1.75 | 1.62 | 1.67 | 1.64 | 2.03 |
| | 20 | 0.84 | 27.19 | 6.21 | 6.80 | 6.97 | 7.22 | 1.80 | 1.62 | 1.64 | 1.59 | 2.31 |
| **Demand function from regression model (1)** | | | | | | | | | | | | |
| Pharmacy-only | 5 | 0.7 | 23.63 | 4.83 | 5.87 | 6.27 | 6.66 | 2.37 | 2.91 | 2.63 | 2.13 | 1.97 |
| | 10 | 0.7 | 24.33 | 5.15 | 6.08 | 6.35 | 6.75 | 2.97 | 3.55 | 3.14 | 2.71 | 2.61 |
| | 20 | 0.7 | 24.82 | 5.46 | 6.15 | 6.36 | 6.85 | 3.82 | 4.14 | 3.91 | 3.65 | 3.66 |
| | 5 | 0.84 | 25.65 | 5.46 | 6.44 | 6.7 | 7.05 | 2.10 | 2.52 | 2.28 | 1.90 | 1.80 |
| | 10 | 0.84 | 26.24 | 5.75 | 6.55 | 6.79 | 7.15 | 2.30 | 2.76 | 2.42 | 2.04 | 2.08 |
| | 20 | 0.84 | 26.56 | 5.91 | 6.61 | 6.83 | 7.2 | 2.47 | 2.79 | 2.48 | 2.21 | 2.44 |
| Pharmacy + Dollar | 5 | 0.7 | 25.51 | 5.54 | 6.39 | 6.61 | 6.97 | 2.00 | 2.18 | 2.08 | 1.89 | 1.91 |
| | 10 | 0.7 | 25.75 | 5.72 | 6.40 | 6.64 | 7.00 | 2.49 | 2.52 | 2.63 | 2.37 | 2.45 |
| | 20 | 0.7 | 25.81 | 5.81 | 6.43 | 6.6 | 6.96 | 2.96 | 3.05 | 2.93 | 2.94 | 2.95 |
| | 5 | 0.84 | 26.86 | 6.01 | 6.74 | 6.93 | 7.19 | 1.60 | 1.63 | 1.63 | 1.55 | 1.60 |
| | 10 | 0.84 | 27.15 | 6.16 | 6.78 | 6.96 | 7.25 | 1.66 | 1.70 | 1.68 | 1.59 | 1.68 |
| | 20 | 0.84 | 27.2 | 6.18 | 6.79 | 6.98 | 7.26 | 1.67 | 1.72 | 1.67 | 1.59 | 1.70 |