Optimal COVID-19 Vaccination Facility Location

Fernanda Bravo, Jingyuan Hu, Elisa Long
UCLA Anderson School of Management, Los Angeles CA 90095
fernanda.bravo@anderson.ucla.edu, jingyuan.hu.phd@anderson.ucla.edu, elisa.long@anderson.ucla.edu

Problem Definition: Socioeconomic disparities in COVID-19 vaccination rates are partially attributable to poor vaccination site selection, often requiring excessively burdensome travel distances among some communities. In early 2021, the U.S. federal government launched partnerships with several retail pharmacy chains to provide additional vaccine access points, yet these locations are inefficiently selected. We consider an optimal facility location problem with existing retail pharmacy stores and proposed dollar stores as candidate vaccination locations as a mechanism to mitigate travel distance disparities across demographic groups.
Methodology/Results: We formulate this problem as a large-scale mixed-integer program with an objective of minimizing average travel distance to a vaccination site while covering all demand. Assigning each census tract to a vaccination site(s), we measure the resulting travel distance by jurisdiction and demographic group. Results indicate that replacing some of the 58,000 existing vaccination sites with optimally selected dollar stores could reduce average travel distances nationwide by 62%, with several states (Nebraska, Kansas, Missouri, Illinois and South Dakota) improving by 80% or more. Using a newly constructed distance Gini coefficient, we find substantial reductions in travel disparities by racial group, with the largest gains in Illinois, Tennessee, Nevada and Texas. Varying the number of potential stores and vaccination-capacity per store suggests that selecting *where* to strategically locate is more critical than altering the *quantity* or *capacity* of stores. Using cross-sectional and panel vaccination data for California—and exploiting variation in the opening and closures of mass vaccination sites—we document empirical evidence of a strong negative relationship between travel distance to a vaccination site and vaccination uptake.
Managerial Implications: Our study offers an interpretable, quantitative framework that can help federal and state health departments with future vaccination site selection to improve booster vaccine access, particularly for marginalized populations.

Key words: COVID-19, Vaccine access, Facility location, Equity, Mixed-integer programming

1. Introduction

With 275 million confirmed cases and more than five million deaths worldwide, the ongoing COVID-19 pandemic has adversely affected global health outcomes, stifled economic growth, and drastically altered life in every community around the world (World Health Organization 2021). The pandemic ushered in an unparalleled period of new vaccine technologies, with global efforts to develop and distribute an effective vaccine producing several effective options in less than a year (Graham 2020). Three vaccines (Pfizer-BioNTech, Moderna, and Johnson & Johnson/Janssen) have attained Emergency Use Authorization by the U.S. Food and Drug Administration, and every American over age five is now eligible to receive a COVID-19 vaccine (CDC 2021a). Nevertheless, difficulties in scheduling an appointment or traveling to a vaccination site present significant obstacles within some communities. Improving the vaccine distribution process to better match demand and supply will be increasingly important as a third dose booster vaccination is widely recommended amidst the growing presence of the Omicron variant in December 2021 (Roberts 2021b).

To improve COVID-19 vaccination access, in February 2021 the U.S. government launched the Federal Retail Pharmacy Program, a collaboration between the federal government, states, and territories, and 21 national pharmacy partners and independent pharmacy networks that includes about 40,000 retail locations nationwide (CDC 2021b). Pharmacy partners were also deployed to long-term care facilities to vaccinate residents and staff, a widely supported program given that pharmacists are highly trusted and trained healthcare providers with direct knowledge of their patient populations. With nearly 90% of Americans living within five miles of a pharmacy, these partnerships offered convenient access for many individuals to obtain a free COVID-19 vaccine at a local pharmacy in their community (Berenbrok et al. 2021). The program improved vaccine uptake while decreasing the logistical and operational burden on local health departments.

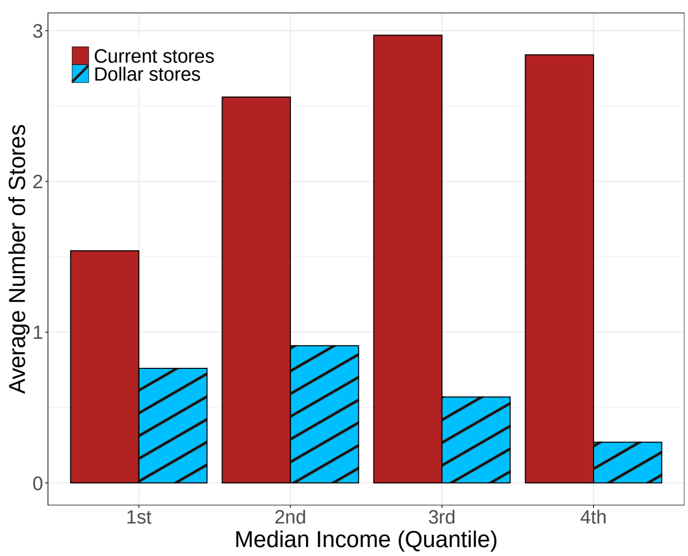
Despite early progress in expanding vaccine availability in the U.S., some populations continue to face barriers to accessible COVID-19 vaccination. Individuals who reside more than five miles from a pharmacy or who have limited transportation access or time off from work may find even a relatively short travel distance overly burdensome. In spring 2021, The Washington Post reported:

> "*Some 9 million Americans live further than 10 miles from the closest vaccine administration site. Requiring even one person to travel outside of their community to access the vaccine is a burden but asking this of millions of Americans is its own public health emergency.*"
>
> – Sean Dickson, Director of Health Policy at the West Health Policy Center

Known as *vaccine deserts*, these communities have lower vaccination rates and disproportionately occur among low-income and minority groups—the populations most afflicted by COVID-19 (McPhillips and Krishnakumar 2021, Del Rio 2020). Among Black and Hispanic Americans, hospitalization rates are 2.5 times higher and COVID-related deaths are double that of White Americans, highlighting the urgent need to reduce vaccination barriers (CDC 2021c). As of December 2021, approximately two-thirds of the U.S. population had received at least one COVID-19 vaccine dose, but with wide disparities in uptake by race: Asian (77%), White (58%), Hispanic (56%), and Black (51%) (Ndugga et al. 2021, McPhillips and Krishnakumar 2021). Further, COVID-19 vaccination uptake is lower in rural counties (38.9%) than in urban counties (45.7%) (Murthy et al. 2021), with highly diverse rural communities (counties where one-third or more of the population belongs to a racial or ethnic minority group) experiencing 1.6 times more COVID-19 deaths per capita than other rural counties (Bradford et al. 2021). Identifying geographic areas with limited vaccination access points is therefore essential to mitigate disparities and ensure equitable access for all populations.

Realizing these challenges, the director of the CDC and the company Dollar General, one of the country's largest discount retail chains, confirmed reports of a potential partnership through which COVID-19 vaccines would be administered in Dollar General's retail locations. Widely popular for discounted prices and selection of essential products, much of Dollar General's success has come from locating in places with little competition from other retailers. During times of urbanization, they have established themselves in struggling rural communities with limited investment from other retailers (Wolfrath et al. 2018). Dollar General operates more than 17,000 stores in 46 states—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 2021a). Two other discount chains, Dollar Tree and Family Dollar, each operate more than 7,000 stores. Most importantly, these discount stores tend to locate in lower-income communities, precisely the areas most underserved by existing retail pharmacies (Figure 1), creating opportunities to greatly improve vaccine access for low-income households (Chevalier et al. 2021). In August 2021, nine counties in Michigan began partnering with Dollar General stores to host community COVID-19 vaccine clinics (Detroit Free Press 2021). Although the ubiquity of dollar stores in the U.S. provides a broad set of alternative vaccination sites, it remains unclear to what extent adding these retail stores to the current federal vaccination program might improve access 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 ending the pandemic.

Figure 1 Current retail pharmacy stores and dollar stores, by median household income, per California zip-code.



Note. Data source: U.S. Census 2014-2018 American Community Survey (US Census Bureau 2019)

In this paper, we examine high-level decision-making by state and federal governments on partnering with large retail chains (dollar stores) to provide COVID-19 vaccination access. Using a facility location model, we assign more than 70,000 U.S. census tracts to one or more of the 90,000 candidate vaccination sites, demonstrating how dollar stores could augment the existing network of pharmacy partners offering COVID vaccination under the current federal program. Our model identifies the optimal set of vaccination locations within each state—without increasing the total number of initial sites—and quantifies the improvement in average travel distance and reductions in travel disparities by racial group. The contributions are as follows:

- We formulate the vaccination site location problem as a large-scale mixed-integer program, where retail stores (pharmacies and dollar stores) are candidate locations. The objective minimizes the average travel distance between census tracts and their optimally matched vaccination site(s). Racial disparities in travel distance are measured using a newly constructed Gini coefficient, quantifying potential gains in equitable vaccination access. To our knowledge, our study is the first to examine disparities in COVID-19 vaccination access due to travel distance using a facility location optimization model.
- Solving the optimization model using real store location and demographic data for the 48 continental U.S. states and the District of Columbia, we find that adding dollar stores to the current federal pharmacy partnership program could substantially decrease average travel distance to vaccine sites, across all jurisdictions and racial groups. Despite wide variability in baseline Gini coefficients, expanding the set of feasible vaccination locations to include dollar stores reduces inequality in nearly every jurisdiction.
- We conduct detailed numerical case studies on several U.S. metro areas to illustrate our modeling approach and to identify high-priority regions where "vaccination deserts" contribute to poor vaccine uptake. We examine alternative store-capacity strategies and find that selecting *where* to strategically locate—including or excluding dollar stores—is more important than deciding the number and capacity of each store. Our study provides key insights for federal and state health departments in selecting future vaccination sites, particularly as booster doses are now widely recommended.
- Using both cross-sectional and panel data on COVID vaccinations by zip-code in California, we empirically examine the relationship between travel distance to a vaccination site and vaccination uptake. Our study is the first to document a significant *causal* relationship between proximity to vaccination locations and uptake, using a time-series analysis that exploits variation in the openings and closures of mass vaccination sites in early 2021. Such empirical evidence supports our choice of travel distance as a suitable objective function in our facility location model.

2. Literature Review

The present study relates to three streams of literature in operations management: healthcare facility location, vaccine rationing, and the equitable allocation of resources in healthcare.

Healthcare facility location. The optimal facility location problem has been extensively studied within the wider OM community and in the healthcare context, but limited research exists on optimal vaccination site selection during a pandemic. We refer the reader to Daskin and Dean (2005) and Ahmadi-Javid et al. (2017) for detailed reviews of facility location modeling in healthcare, and here we discuss the recent research focusing on COVID-19.

Basciftci et al. (2021) propose a stochastic program and distributionally robust optimization approach to select the locations of resource distribution centers, capacities, shipment amounts, and inventory levels under spatio-temporal uncertainties of disease transmission and demand for resources. Using real COVID-19 infection data, the authors numerically examine vaccine distribution in the U.S. and test-kit distribution in Michigan under different scenarios. Bertsimas et al. (2021) similarly combine a predictive compartmental epidemic model with a high-level optimization model to select mass vaccination sites across the U.S., as well as assigning populations to different sites and allocating vaccines by age group. Their proposed solution could significantly reduce COVID-related death rates and is highly robust to uncertainties and forecasting errors. Similar studies use math programming to optimally select vaccination sites in other countries under different objectives and scenarios (Leithaeuser et al. 2020, Buhat et al. 2021, Tavana et al. 2021). Relatedly, Rastegar et al. (2021) consider a distribution center and storage facility location problem with inventory decisions to determine equitable influenza vaccine distribution during the COVID-19 pandemic. Castillo-Neyra et al. (2021) optimally select vaccination sites for use during a zoonotic epidemic in animals, and using a small case study for a county in Peru, they estimate vaccination likelihood based on owners' walking distance to the nearest vaccination point.

In contrast to Basciftci et al. (2021) and Bertsimas et al. (2021), our work focuses on longer-run decision-making at the national or state-level, with thousands of retail stores serving as candidate locations versus dozens of mass vaccination sites, highlighting the sizeable difference in the scale of our optimization model. In particular, our model optimally selects from more than 58,000 existing vaccination sites, along with 32,000 potential dollar store locations operated by Dollar General, Dollar Tree, or Family Dollar. The solution found by Bertsimas et al. (2021) proposes between one and ten mass vaccination sites per state, amounting to 100 total sites nationwide. Compared to mass vaccination sites (e.g., Dodger Stadium in Los Angeles), retail stores offer more convenience given their proximity to residential communities. As COVID-19 booster shots become widely demanded, given the evidence of waning immunity (Baraniuk 2021), recurrent COVID vaccination, similar to annual flu boosters, will likely become a reality, particularly in the presence of emerging variants like Delta and Omicron (Rubin 2021, Levine-Tiefenbrun et al. 2021, Roberts 2021b). Our optimization model provides interpretable results and could be readily updated with additional vaccination sites such as schools, places of worship, post offices, or other chain retailers.

Vaccine rationing. The COVID-19 pandemic has renewed interest within the healthcare OM community in decision-making around vaccine distribution and dose allocation. Various approaches have investigated key questions relating to which dosing regimen should be considered and which populations should be prioritized, given a limited supply and other constraints. Babus et al. (2020) consider a joint COVID-19 vaccine allocation and stay-at-home order problem over different age-occupation groups with an objective of minimizing infection risk and economic losses. They demonstrate that vaccine allocation should emphasize age-based mortality risk more than occupation-based exposure risk. Matrajt et al. (2020) develop a non-interacting, age-stratified susceptible-exposed-infected-removed (SEIR) epidemic model for allocating vaccines to different age groups. The optimal solution allocates low-efficacy vaccines first to older groups (with higher mortality risk), but allocates high-efficacy vaccines first to younger groups (with higher transmission risk). Chen et al. (2020) consider a dynamic multi-period model with mixing across groups and obtain a similar optimal static policy, but show that dynamic policies generally perform better than static ones. Accounting for uncertainty in disease spread using a riskiness index, Fu et al. (2021) combine a stochastic epidemiological model with robust optimization to minimize the variation in number of infections. The resulting optimal policies prioritize different age groups based on interaction and transmission rates.

Several papers combine data-driven predictive epidemic models with prescriptive optimization-based models, to simultaneously forecast the epidemic trajectory and allocate limited resources such as vaccines. Bennouna et al. (2021) combine a machine learning-based epidemic model with an optimization model to allocate vaccine doses across geographic areas and multiple periods. The model is currently used by the CDC in generating epidemic forecasts as new data become available. Optimizing the allocation of COVID-19 testing kits and subsequently vaccines, Thul and Powell (2021) propose an exploration-exploitation approach where testing kits are deployed to learn the status of the pandemic across different regions so vaccines can be better allocated based on updated beliefs of local infection rates.

The preceding papers consider a single decision-maker aiming to minimize infections and the associated costs, while other papers employ different approaches. With multiple, international decision-makers, Rey et al. (2021) propose a data-driven optimization approach based on Thompson sampling to solve the allocation problem in an online fashion, assuming uncertain vaccine efficacy. Chen et al. (2021) propose allocating COVID-19 vaccines to individuals based on the structural properties of their underlying social contact network. They show that prioritizing vaccinations based on network degree and total contact time is more effective than the current age-based policy, providing significant reductions in disease incidence, mortality, and hospitalizations. Carmen Munguía-López and Ponce-Ortega (2021) present a simple optimization model with different fairness schemes for vaccine allocation among multiple geographical regions, and test social welfare schemes using a case study in Mexico.

Other recent papers have focused on vaccine inventory management and dose allocation. Mak et al. (2021) design several dynamic stocking policies for two-dose COVID-19 vaccine administration to determine the number of vaccines needed for second doses under deterministic vaccine supply. Their analytical results show that releasing all doses generates lower disease transmission than holding back the second doses. Stretching the time between the first and second dose administration is even more effective in reducing new cases, hospitalizations, and mortality. The authors show that a single-dose vaccine, even with an overall lower efficacy, can be more effective in infection control. Shumsky et al. (2021) examine vaccine stockpiling policies to minimize the average time to complete a two-dose regimen under supply uncertainty. They propose a simple policy of reserving some vaccines for second doses that are nearly due, and allocating remaining vaccines as first doses.

Equitable allocation of resources. Our study examines racial and geographical disparities in vaccine access during the pandemic, a key outcome not previously evaluated in the aforementioned studies (Basciftci et al. 2021, Bertsimas et al. 2021). The critical topic of disparities in healthcare has seen growing interest in the OM research community, in the context of organ transplantation (Ata et al. 2017, Wang et al. 2021), decision support systems (Ganju et al. 2020) and medical appointment scheduling (Samorani et al. 2021). Ganju et al. (2020) use information systems to reduce differences in amputation rates between Black and non-Black patients with diabetes. Using data from a large healthcare provider, Samorani et al. (2021) find that current medical appointment scheduling algorithms result in Black patients waiting 30% longer to see a provider, likely due to excessive burdens in traveling to appointments. They propose machine learning-based solutions to eliminate scheduling bias between racial groups.

While equity in *health outcomes* has been widely studied, few studies within the OM literature have examined equity in *vaccine access*. Enayati and Özaltın (2020) combine a dynamic compartmental model with a mathematical program to maximize total influenza vaccines distributed. Using a Gini coefficient-based equity constraint, they find that a balanced vaccine allocation policy with respect to equity and effectiveness is optimal. Rastegar et al. (2021) consider an equitable vaccine distribution problem during an influenza pandemic and maximize the minimum delivery-to-demand ratio per group in each region and over time. Chen et al. (2020) examine the trade-off between equity and efficiency and conclude that a significant number of deaths can be averted by allocating a small fraction of vaccines efficiently instead of equitably. These papers all measure equity using vaccine doses reserved per age subgroup, whereas we evaluate equity in vaccine access by the travel distance to a vaccination site.

Equitable access to COVID-19 testing at the U.S. national and state-level is examined by Risanger et al. (2021) using an optimization model to maximize the number of individuals tested at their closest selected pharmacy. Numerical results show that if COVID-19 testing was offered at all U.S. pharmacies, 94% of the population would be within short distance of a testing site. This estimate, however, represents a best-case scenario as testing site capacity is omitted in their model. Most related to our current study, Chevalier et al. (2021) calculate the average distance to vaccination sites under the current federal program 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 from these studies in several aspects, most notably that we formulate a math program to *optimally select* vaccination sites of limited capacity and compute resulting travel distances, in aggregate and by racial group, at the census tract-level. Using pharmacy location data of active vaccination sites for the entire continental U.S., and locations of three major dollar store chains (Dollar General, Family Dollar, Dollar Tree), our study compares the marginal benefits of expanding the set of feasible vaccination sites to include *more* locations versus *better-selected* locations.

Finally, travel distance requirements to U.S. vaccination sites are estimated by Berenbrok et al. (2021). Despite one-half of all Americans living within one mile of a potential vaccination site (e.g,. community pharmacies, federally qualified health centers, hospital outpatient units, and rural health clinics), wide disparities exist between Black and White residents, with many counties in Georgia, Mississippi, Alabama, Louisiana, Texas, and Virginia requiring travel distances in excess of 10 miles for most Black residents. We similarly document COVID-19 vaccination travel disparities at the zip-code level in California. Additionally, to our knowledge, our study is the first to empirically examine the relationship between travel distance and vaccination uptake—an important finding on its own and one that supports our choice of objective function.

3. Model

We construct a vaccination facility location model to assign each population to one or more vaccination sites, and compute the resulting travel distance. Rather than explicitly model COVID-19 transmission dynamics or various sources of heterogeneity and uncertainty, our model investigates a high-level strategic decision faced by a decision-maker: Given the current federal pharmacy vaccination program, how would partnering with dollar stores (or other retail chains) improve vaccination access? In short, we consider a simplified setting where everyone is offered a single dose (e.g., booster shot or seasonal shot) and dollar stores are added to the set of feasible vaccination sites. We present our vaccination site location model in section 3.1 and describe our data sources in section 3.2. Assumptions and details for our numerical study are given in section 3.3.

3.1. Formulation

Consider a single state (e.g., California) consisting of census tracts $\mathcal{J}$ and possible locations for vaccination sites $\mathcal{I}$. Our goal is to assign the entire population of each census tract, also referred as a community, to one or more sites to minimize the state-average required travel distance to a vaccination site. Each census tract is roughly equivalent to a neighborhood, with an average population of 4,000 residents and no more than 8,000 residents (US Census Bureau 2019). Similar to Bertsimas et al. (2021), we assume that vaccinations only occur in a resident's home state, because the national facility location problem is computationally intractable—requiring assigning 72,000 communities to at least one of the 90,000 potential vaccination sites—and because it is required in practice for public health monitoring and reporting purposes. We therefore break the problem into 49 subproblems (48 states in the continental U.S. and District of Columbia, excluding Alaska and Hawaii, as there are no dollar stores in these two states), corresponding to the optimal assignment within a state.

We assume a fixed number of active vaccination sites N per state, each with limited vaccine supply $\gamma_i, \ \forall i \in \mathcal{I}$. Each community includes a population of $d_j, \ \forall j \in \mathcal{J}$ residents and the travel cost (i.e., distance) between community j and vaccination site i is $c_{ij}, \ \forall j \in \mathcal{J}, \ i \in \mathcal{I}$.

We introduce the following decision variables:

$$z_i = \begin{cases} 1 & \text{if vaccination site } i \in \mathcal{I} \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij} = \text{proportion of demand from community } j \in \mathcal{J} \text{ satisfied by vaccination site } i \in \mathcal{I}$$

The vaccination facility location problem for a single state is formulated as follows:

$$(\mathcal{P}) \quad \min \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} d_j y_{ij} c_{ij} \tag{1}$$

$$\text{s.t.} \sum_{j \in \mathcal{J}} d_j y_{ij} \leq z_i \gamma_i, \quad \forall i \in \mathcal{I} \tag{1a}$$

$$\sum_{i \in \mathcal{I}} y_{ij} = 1, \quad \forall j \in \mathcal{J} \tag{1b}$$

$$\sum_{i \in \mathcal{I}} z_i = N \tag{1c}$$

$$y_{ij} \in [0,1], \quad z_i \in \{0,1\} \tag{1d}$$

The objective function (1) minimizes the average travel distance between census tracts and their assigned vaccination site(s). Constraints (1a) ensure that total demand assigned to each vaccination site does not exceed its capacity. Constraints (1b) ensure that the entire population of a census tract is covered, but note that (1a) implies that multiple vaccination sites can be used to serve each census tract. Constraint (1c) imposes a total budget of N active vaccination sites for the state. Note that $\mathcal{P}$ is a mixed-integer program, where y_{ij} is a continuous variable between 0 and 1 and z_i is a binary decision variable. This is essentially a capacitated $p-$median facility location problem (ReVelle and Swain 1970), as we assign capacities to each location, and optimally locate N facilities to minimize the weighted average distance. We discuss in detail the explicit and implicit assumptions used in this formulation along with our parameter estimation in section 3.3.

3.2. Data Sources

We utilize geospatial data from multiple sources. First, we collect location data (latitude and longitude) for the three biggest dollar store chains (Dollar General, Dollar Tree, and Family Dollar) from ScrapeHero (2021), which comprises more than 32,000 store locations. Second, all 58,000 existing COVID-19 vaccination locations are scraped from the CDC's website (`https://www.vaccines.gov/`). Finally, we obtain the demographic and socioeconomic data for more than 72,000 tracts from the Census Bureau's Tract Level Planning Database (PDB), which is extracted from the 2010 Census and 2019 American Community Survey (ACS) databases (US Census Bureau 2019). Similarly, the centers of population by census tract are also obtained from US Census Bureau (2019). For visualization, we obtain tract shapefiles from the U.S. Census API (US Census Bureau 2021).

3.3. Parameter Estimation and Assumptions

We calculate the travel cost from the population centroid of each tract to every candidate vaccination location using the Euclidean distance. This effectively assumes that all tract residents share the same travel distance to any given site, a reasonable assumption because tracts are generally geographically small (i.e., 80% of census tracts are less than 20 square-miles in area). Vaccine demand within a tract is assumed to equal its population, which allows for everyone to get a shot regardless of current vaccination rates. This corresponds to the scenario of assigning residents to vaccination sites for a booster shot, ensuring that everyone has access to a nearby vaccination site.

The capacity of a single vaccination site γ_i is assumed to be homogeneous within a state ($\gamma_i = \gamma$ for all i), but can vary across states or other jurisdictions. Specifically, for a given state we derive the store capacity by:

$$\gamma = 1.2 \times \frac{\text{Population of the state}}{\text{Number of current vaccination sites in the state}}$$

One can think of this as the implicit capacity needed to cover all demand in a state, given the set of current vaccination sites. We multiply by a scaling factor of 1.2 to allow for inefficiency in the current choice of locations and to guarantee that the model is always computationally feasible. Varying gamma does not significantly change our findings, as long as the facility assignment problem is feasible.

Appendix Table A1 summarizes the number of potential vaccination locations and implied capacity per store, by state. The number of existing vaccination sites ranges from $N = 102$ in Wyoming to $N = 4,035$ in California, while the number of dollar stores ranges from six stores in the District of Columbia to 3,332 stores in Texas. Of note, each state's optimal solution selects exactly N stores, the number of current vaccination sites in operation. 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. Of course, in reality, we may prefer to operate fewer stores to reduce overhead costs. In sensitivity analysis in section 4.3, we examine the effects of increasing or decreasing the total number of stores and vaccination capacity per store.

Finally, we assume that residents receive a vaccination at their assigned vaccination site, which is not necessarily the closest location. We also ignore heterogeneity in efficacy or vaccine 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 strategy.

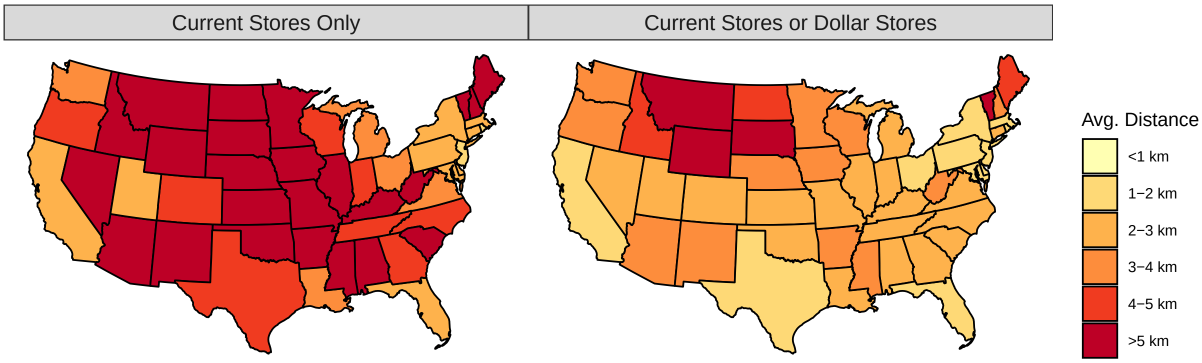
4. Results

We solve the optimal vaccination location problem, holding constant the total number of locations selected in each state, under two sets of feasible locations: (i) current pharmacy stores only and (ii) current pharmacy stores and dollar stores. Scenario (i) serves as a benchmark analysis of the current U.S. vaccination system, where census tracts are optimally assigned to vaccination site(s) to minimize aggregate travel costs. Of course, actual travel distances realized under the current system are likely greater as residents can choose where to receive a vaccine. Our analysis, however, allows us to document the performance of each state under the optimistic scenario (i) and to estimate how adding dollar stores as potential sites in scenario (ii) affects average travel distances and disparities. We use Gurobi 9.1 (Gurobi Optimization 2021) coded in Python 3.8.5 for solving the resulting mixed-integer program. Our numerical study is performed on a MacOS 10.15 server with 16 GB RAM and Intel 2 GHz processor. Computational runtimes ranged from 0.1 hours in Wyoming ($N = 151$ current or potential vaccination sites and $|\mathcal{J}| = 132$ census tracts) to 5 hours in California ($N = 5,051$ current or potential vaccination sites and $|\mathcal{J}| = 8,057$ census tracts).

4.1. Average Travel Distance to Vaccination Sites

Figure 2 illustrates the average travel distance between home census tracts and their optimally assigned COVID vaccination site(s) for the continental U.S. under both scenarios. The sharp contrast indicates significant reductions in travel distance for most states. The optimal solution replaces more than $22,000$ pharmacy stores with dollar stores—40% of existing locations—yielding an average improvement in travel distance of 62% nationwide.

Figure 2 **Travel distance from home census tracts to optimally assigned COVID vaccination site.**

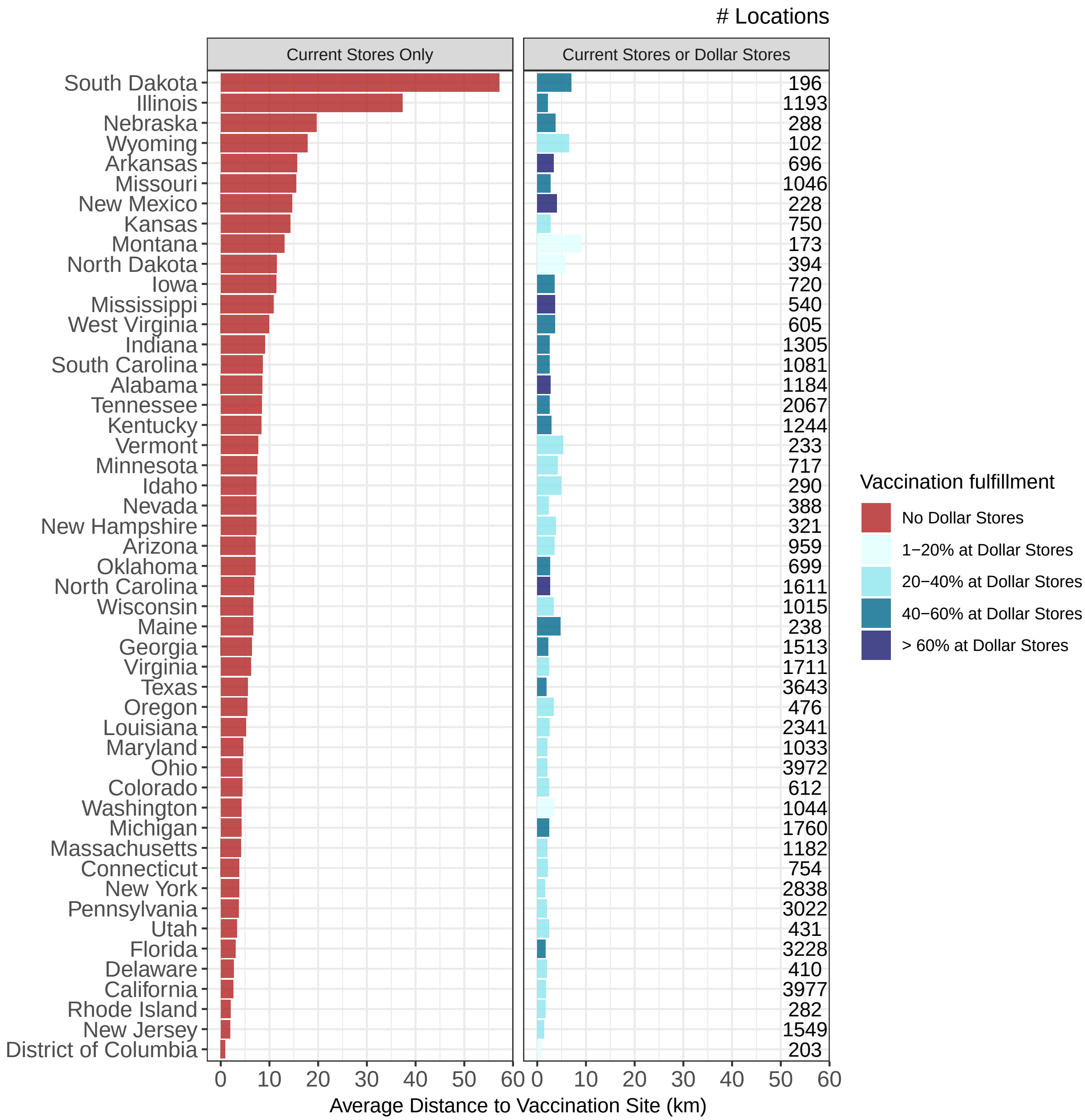


Rural states tend to perform poorly under the current set of vaccination locations. Even though the addition of dollar stores generates sizeable improvements in some rural states (e.g., Montana, South Dakota, Wyoming), travel distances remain greater than 5km, highlighting the need for other vaccination access points, such as mobile clinics, to increase coverage in isolated areas. Some populous, urban states similarly witness substantial improvements, given the prevalence of vaccine deserts throughout the jurisdiction. South Dakota, a rural state with 57% of its population residing in rural areas, and Illinois, a populous state with 88% of its population living in urban areas, both obtain nearly eight-fold reductions in mean travel distance when dollar stores are included in the feasible set.

Figure 3 shows the average travel distance of all jurisdictions, as computed by our facility location model under the two scenarios, with the proportion of vaccinations hypothetically fulfilled by dollar stores (detailed results for all states are reported in Appendix Table A1). Distance to a vaccination site varies considerably by state under the current set of locations, ranging from only 0.9km (District of Columbia) to 57.2km (South Dakota), with a population-weighted national average of 6.2km. Illinois and South Dakota observe the greatest improvements in travel distance, dropping from 14.0km to 1.8km and from 57.2km to 6.7km, respectively. States with greater average travel distance under the existing set of locations tend to replace more pharmacy locations with dollar stores, as expected. The highest proportion of vaccinations assigned to dollar stores occurs in Mississippi (77%), Alabama (63%), New Mexico (62%), and Arkansas (61%). Except for New Mexico, these states are mostly rural with only 50-60% of their population situated in urban areas.

We intuitively observe that states with larger populations or those with more dollar stores in operation also include more dollar stores in the optimal solution. Texas (3,673 current stores, 3,332 dollar stores), Ohio (3,989 current stores, 1,670 dollar stores), and Florida (3,328 current stores, 2,088 dollar stores) would each open over a thousand dollar stores under the proposed

Figure 3 **Travel distance of each state (with and without dollar stores).**



solution. Including dollar stores as potential sites theoretically always reduces travel costs, yet the improvement is relatively modest in states currently performing well, and these states tend to keep their existing vaccination sites. For example, only 20% of demand is covered by dollar stores in New Jersey (average travel distance drops from 1.9km to 1.4km) and California (average travel distance drops from 2.4km to 1.8km). In the District of Columbia (average travel distance drops from 0.94km to 0.87km), dollar stores add minimal value, largely because of the small, dense geographic area and the availability of only six dollar stores in the region.

One striking observation is that, even with only a few dollar stores selected, average travel distance dramatically decreases if the dollar stores are located in vaccine deserts. Current vaccination sites are not uniformly distributed over geographic areas nor perfectly population-weighted. In several states, residents living in a few tracts located in vaccine deserts face unreasonably high travel costs, driving up the state average, and adding a few locations to these underserved areas significantly reduces average distance travelled. In North Dakota, for example, only 18% of vaccination demand is assigned to the 76 dollar stores optimally selected by the optimization model, yet average travel costs are reduced by 48%, from 11.5km to 5.9km. We observe similar patterns in other geographically large, mostly rural states including Montana, Idaho, South Dakota, Kansas, and Nebraska, as shown in Figure 3.

4.2. Racial Disparities

Observing that adding dollar stores could substantially reduce vaccination travel requirements, a natural question to ask is: To what extent does the availability of dollar stores also alleviate racial disparities in vaccine access?

To quantify such disparities in vaccine access, we compute a Gini coefficient for each state under the two aforementioned scenarios, i.e., before and after adding dollar stores to the set of feasible locations. The Gini coefficient is commonly used in economics to measure income inequality in a population, and ranges between zero and one, where a coefficient of zero means perfect equality and a coefficient of one indicates maximal inequality in the population.

Here, we denote $\mathcal{K} = \{\text{Asian, Black, Hispanic, White, Other}\}$ as the set of racial groups, where Other includes American Indian, Alaska Native, Native Hawaiian, and all other racial groups described by the US Census Bureau (2019). The Gini coefficient G for a single state is given by:

$$G = \frac{1}{2\mu} \sum_{i \in \mathcal{I}, k \in \mathcal{K}} \sum_{j \in \mathcal{I}, p \in \mathcal{K}} f(x_{ik}) f(x_{jp}) |x_{ik} - x_{jp}| \tag{2}$$

where x_{ik} is the average travel distance of group k in tract i, and $f(x_{ik})$ is its population proportion in the state. The term $\mu = \sum_{i \in \mathcal{I}, k \in \mathcal{K}} f(x_{ik}) x_{ik}$ is the weighted-average travel distance. Under our model assumptions, the travel distances for all racial groups within a tract are equal, i.e. $x_{ik} = x_{ip}$ for all $i \in \mathcal{I}$, and $k, p \in \mathcal{K}$. This may not hold in reality as geographic segregation may exist within tracts. However, since census tracts are generally small, the difference in distance among residents within a tract is minimal relative to distances between tracts. In our optimization model, recall that we do not impose any constraints regarding racial equity in distances travelled. Thus, there is no theoretical guarantee that the resulting solution improves equity among racial subgroups.

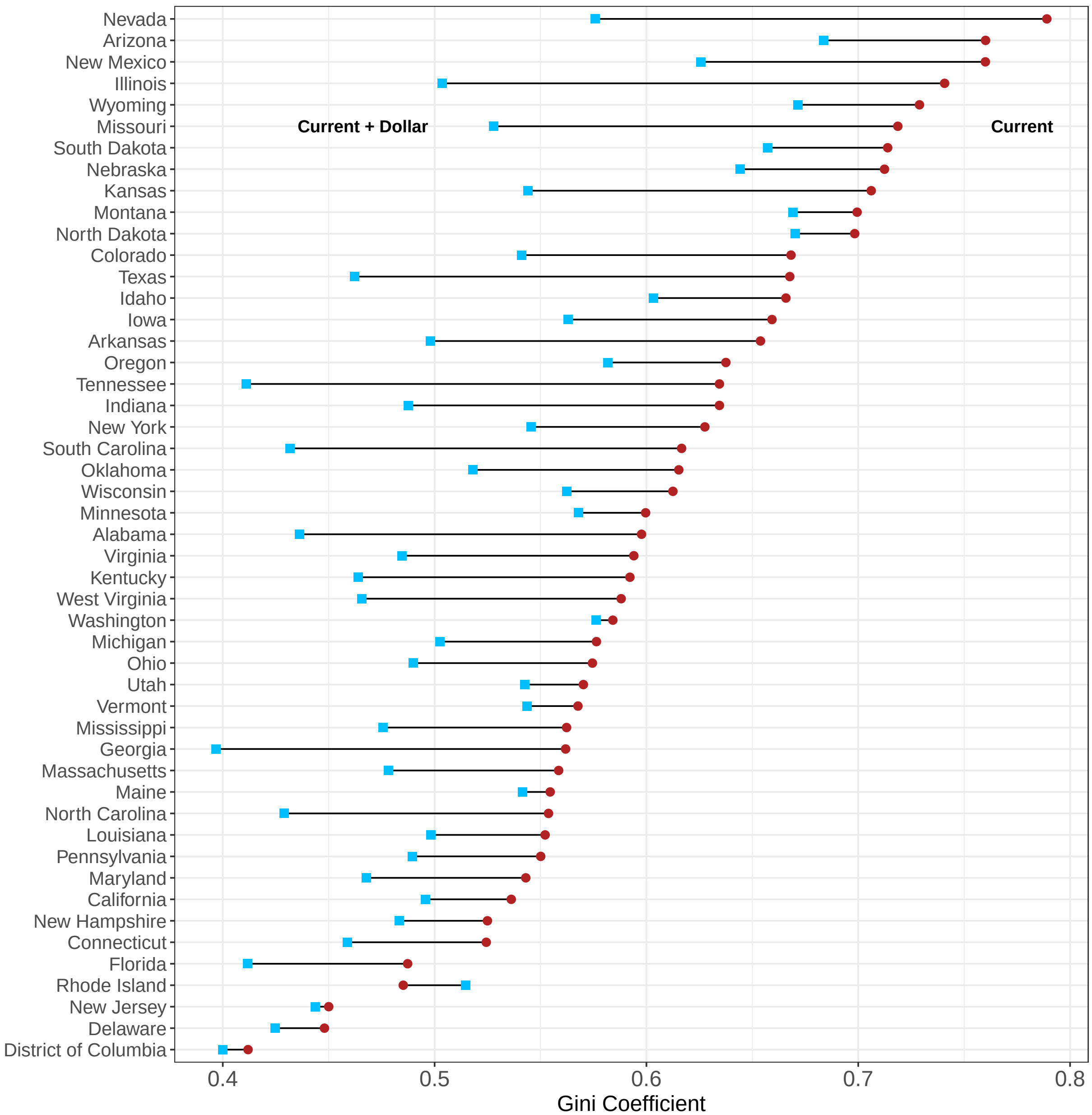
The addition of dollar stores decreases Gini coefficients in every state except Rhode Island, as depicted in Figure 4. The U.S. average Gini drops from 0.60 to 0.50, with more than half of states incurring a Gini of less than 0.5. Under the current system, Nevada (0.79), Arizona (0.76), and New Mexico (0.76) have the highest Gini coefficients, while the District of Columbia (0.41), Delaware (0.45), New Jersey (0.45) have the lowest, aligning with our prior observation that regions that are more populous, geographically larger, or with more diffuse vaccination sites witness greater improvements in Gini coefficients. In general, states with higher Gini coefficients experience greater reductions with dollar stores introduced—given the greater opportunities for improvement—although this is not guaranteed. Georgia and North Carolina, for instance, have below-average Gini coefficients, yet replacing some current locations with dollar stores further reduces disparities in both states. Conversely, dollar stores minimally improve racial disparities in Montana and North Dakota, as previously noted. Nonetheless, we find a positive correlation between improvements in Gini coefficients and percentage demand assigned to dollar stores (see Appendix Figure B1), supporting our earlier observation that the marginal benefits of adding dollar stores depend on their actual locations within each state. The only Gini coefficient that does not improve is in Rhode Island, where travel distance modestly decreases from 2.0km to 1.7km, but travel disparities slightly worsen as the optimal solution shifts vaccination locations.

To visualize the improvement in distance travelled for each subgroup, we examine four states: California, Florida, Illinois, and New Jersey (Figure 5). As previously noted, actual travel distances to vaccination sites may be smaller as the site assigned to each census tract is not necessarily the closest location, given our objective of minimizing aggregate distance subject to per-store capacity constraints. Across the four states, the optimal solution including dollar stores generates sizable reductions in travel distances to vaccination sites for every racial group, with more than half of the population living within 1km of their assigned vaccination site. Consistent with our prior observation, California has not only the lowest overall travel cost but also the lowest travel cost for every racial subgroup among the selected states. Even with California's impressive current selection of vaccination sites, the inclusion of dollar stores shifts the entire distribution across all racial groups, but most notably among Hispanics, Blacks and Other races. Conversely, Illinois currently faces the greatest travel costs, both in aggregate and within each racial subgroup. Fewer than 20% of Black residents in Illinois live within 1km of a vaccination site; replacing just one-third of current sites with optimally located dollar stores could potentially raise this proportion to nearly 90%. In Florida and New Jersey, we spot a remarkable improvement in vaccination travel distances for Hispanic and Black residents, a finding documented in many other states.

4.3. Capacity Consolidation

We extend our optimization model by varying the total number of sites open and the capacity of each site, which were previously fixed for each state. Here, we assume that the total supply of

Figure 4 **Gini coefficient by state (with and without dollar stores).**



vaccines (γN) remains fixed, but the number of selected sites (N) and the capacity per site (γ) can vary. We examine the optimal solution under two scenarios: opening more, smaller vaccination sites (large N, small γ) or opening fewer, larger vaccination sites (small N, large γ). We evaluate our model from $N_{min} = N_{current}/2$ to $N_{max} = N_{current} + N_{dollar}$ in four states (California, Florida, Illinois, and New Jersey) and compute the resulting travel costs. As we permit an optimality gap in solving the mixed-integer program, we also report the best possible objective value, i.e., the lower bound on the average travel cost.

Figure 5 **Distance to vaccination sites by racial group (with and without dollar stores) in select states.**

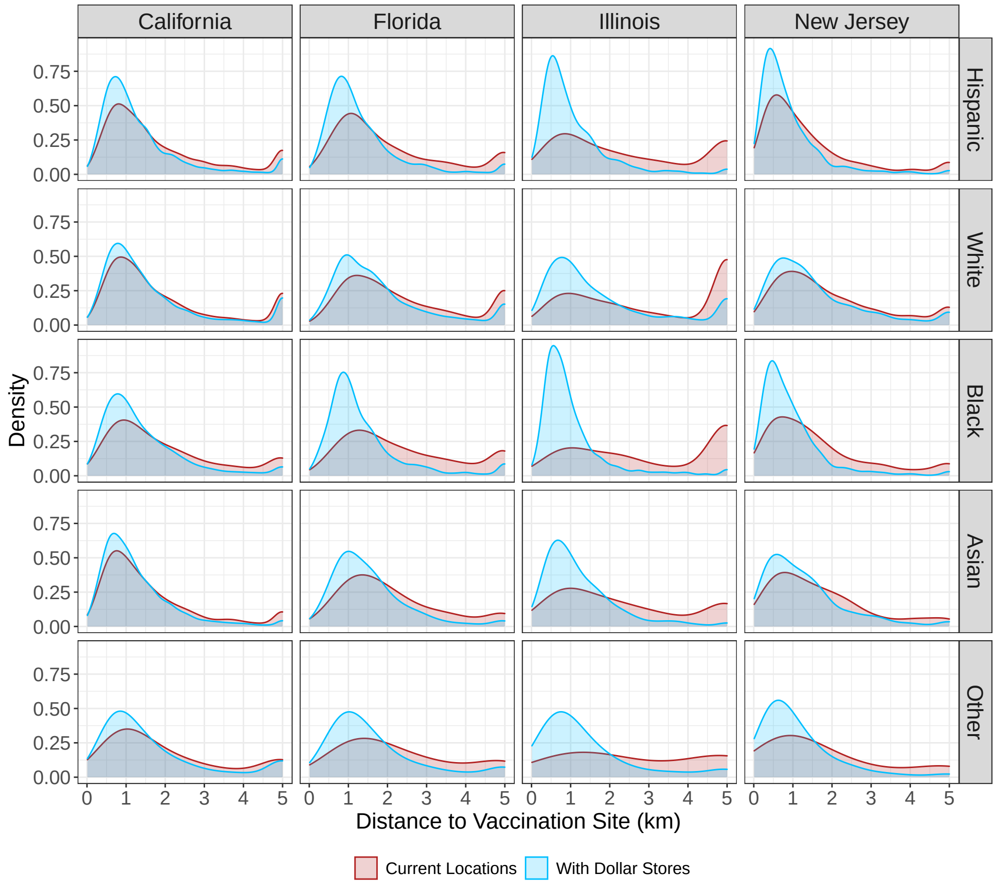
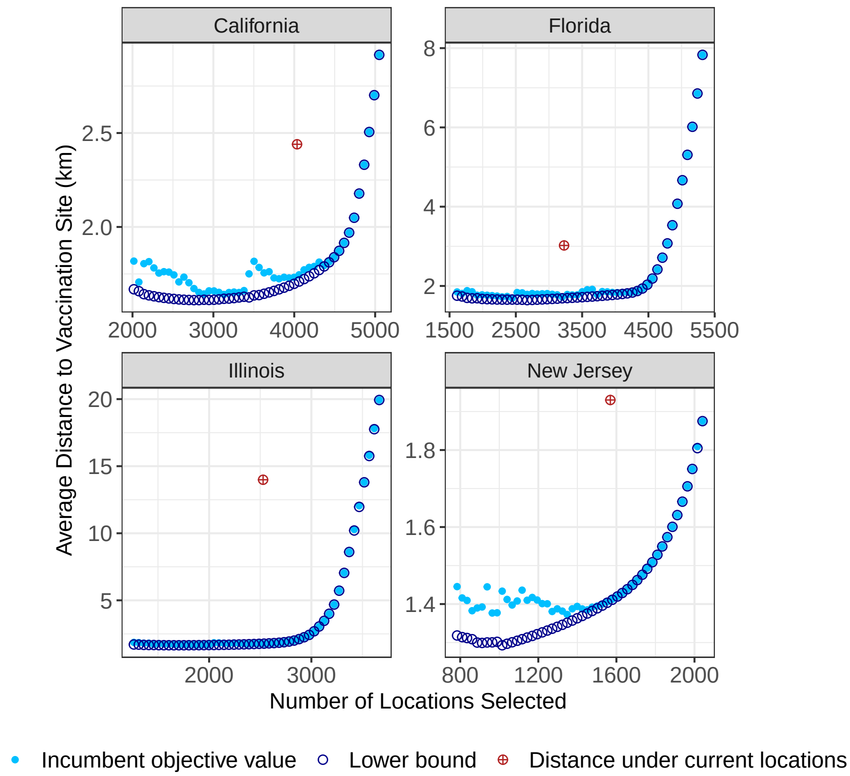


Figure 6 shows the sizeable reductions in travel distances (the vertical shift) in optimally selecting both pharmacies and dollar stores, relative to the current set of locations. If optimally selected, Florida and Illinois could operate 50% fewer vaccination sites without significantly altering average distance travelled, given the spatial overlap of potential locations. California and New Jersey could further reduce travel distances by approximately one-third with operating fewer stores, as the per-store capacity simultaneously increases.

Assuming a fixed supply (γN) of vaccine doses, opening too many or too few stores can result in high travel distances. Too many stores, each with low capacity, leads to shortages in highly populated areas, forcing people to travel further to get vaccinated. On the other hand, too few stores requires longer travel distances, and potentially exacerbates disparities in some communities. Selecting *where* to strategically locate—with or without dollar stores—is more critical than deciding the number and capacity of each store. Optimally selecting the number of stores over the plausible range N_{min} to N_{max} only modestly changes travel distance, whereas replacing existing stores with optimally chosen dollar stores can easily reduce travel costs by one-half (Figure 6).

Figure 6 **Average travel distance under varying numbers of vaccination sites N in selected states.**



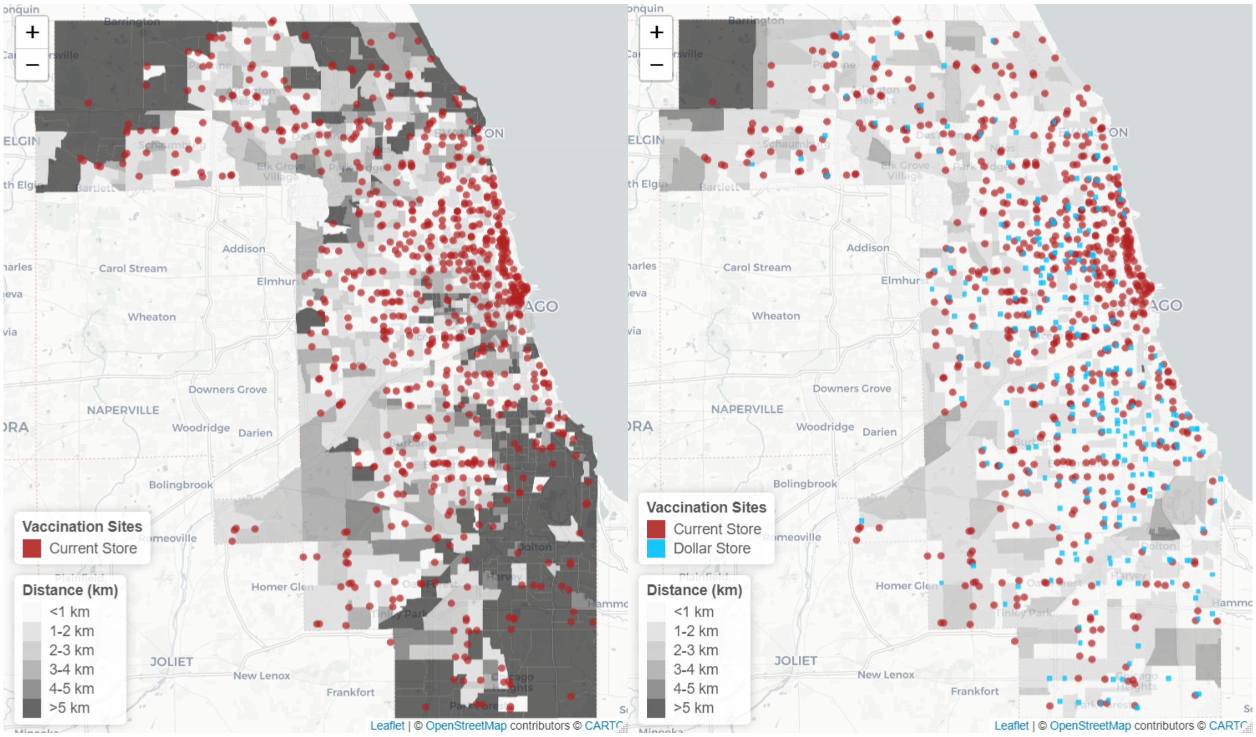
5. Case Study

We illustrate our optimization model formulation with case studies in several metro areas. We first examine Cook County, Illinois (Chicago metro area), the most populous county in the state and second most populous county in the U.S., with more than 5.2 million residents. Historically segregated by race and class, Cook County has recently faced wide gaps in COVID vaccination rates among Blacks and Hispanics compared to White residents (see Appendix Figure B2 for a map of racial composition by neighborhood), making it an ideal setting to examine to what extent optimally selecting vaccination sites might reduce vaccination travel distances and, potentially, mitigate disparities among racial groups.

5.1. Cook County, Illinois

Figure 7 depicts all 724 current vaccination locations (Figure 7a) and the optimally selected sites after considering dollar stores (Figure 7b), holding constant the total number of locations *within the state* at $N = 2,528$. Note, we do not require the number of stores *within the county* to be equal under the two scenarios. In fact, we find that the optimal solution would close 58 current pharmacy locations but add 262 dollar stores, for a net gain of 204 vaccination sites in Cook County. This occurs because locations in other less-populated counties are not selected, given our objective of minimizing aggregate travel distance across the state.

Figure 7 **COVID vaccination sites and average travel distance by tract in Cook County, Illinois.**



(a) Current locations (b) Optimal locations including dollar stores

The maps also show the average travel distance between each census tract and its optimally assigned vaccination site, with darker regions corresponding to distances exceeding 5km. Under the current system (Figure 7a), we clearly observe more vaccine deserts in southside Chicago, where neighbourhoods are predominantly Black or Hispanic, with most residents needing to travel more than 5km to a vaccination site. Most existing vaccination sites concentrate in the central area (e.g., downtown Chicago, northern lakefront areas, and Evanston) where neighbourhoods are mostly White and residents need to travel less than 1km to a vaccination site. This geographic segregation also drives Cook County's high Gini coefficient of 0.75 (Table 1).

Figure 7b shows the optimal selection of vaccination locations after adding dollar stores to the feasible set. In downtown Chicago, the total number of vaccination sites decreases yet, importantly, travel costs for local residents do not worsen, indicating significant geographic redundancy in the current set of vaccination sites. Southside Chicago, in contrast, faces high travel distances and the optimal solution adds many additional dollar stores, reducing distances to less than 2km for most tracts. Even if only 10 to 20 dollar stores are strategically added to these areas, most residents of Cook County would see improvements in accessibility, with nearly everyone living within 2km (1.3 miles) of a vaccination site, a distance typically considered walkable. In the suburban parts of Cook County, mainly in the northwest and western areas, we observe an equal distribution of dollar stores and current locations, while the total number of stores opened is nearly identical. These are areas where vaccination supply matches demand but the locations are not optimally selected. In other words, the optimization model replaces about half of current vaccination sites with dollar stores in alternative locations with less geographic overlap.

5.2. Other Metro Areas

We next explore how the model optimally selects vaccination locations in six other U.S. metro areas: Houston and surrounding Harris County (Appendix Figure B3), Los Angeles County (Appendix Figure B4), Miami-Dade County (Appendix Figure B5), Minneapolis-Saint Paul (Appendix Figure B6), New York City (Appendix Figure B7), and Philadelphia County (Appendix Figure B8). Table 1 summarizes the main results for these selected metro areas and Figures 3 and 4 summarize the results for each state.

For regions experiencing severe geographic and racial disparities in vaccination access (Miami-Dade, Minneapolis-Saint Paul, New York), we observe similar results as with Cook County. In New York City, for example, more than $1,000$ vaccination sites currently operate across the five boroughs, yet there is clearly a shortage of locations in the eastern boroughs of Brooklyn, Queens, and the Bronx, home to more Black and Hispanic residents, but an abundance of vaccination sites in Manhattan, creating enormous differences in travel distances. Our optimal solution would open 57 dollar stores in Brooklyn, 43 dollar stores in Queens, and 36 dollar stores in the Bronx, while closing 123 existing sites in Manhattan.

Similar to Chicago and New York City, Miami-Dade County has pockets of limited vaccination access. The optimal solution would open 119 dollar stores and keep 274 of the existing 321 locations, a net increase of 72 locations, mainly concentrated in the predominantly Black and Hispanic neighborhoods northwest of Miami Beach, such as Hialeah. Similarly, Minneapolis-Saint Paul faces a shortage of vaccination access points in the central and southern metro areas. The addition of just 74 dollar stores could substantially reduce the travel burden, with 48% of residents living within 2km of a vaccination site and 72% living within 3km. In Houston (Harris County), while

Table 1 **Results for selected U.S. metro areas.**

	Current Locations				Optimal Locations			
Region	Existing Stores	Dollar Stores	Mean Travel Distance (km)	Gini Coeff.	Existing Stores	Dollar Stores	Mean Travel Distance (km)	Gini Coeff.
Cook County, IL	724	0	6.88	0.749	666	264	0.87	0.351
Miami-Dade County, FL	321	0	2.45	0.532	274	119	1.04	0.347
Los Angeles County, CA	979	0	1.63	0.435	808	153	1.17	0.387
Harris County, TX	577	0	1.99	0.383	333	218	1.14	0.281
Minneapolis-St Paul, MN	372	0	3.52	0.451	275	74	2.21	0.409
New York City, NY	1,073	0	2.05	0.541	915	154	0.67	0.478
Philadelphia County, PA	324	0	1.41	0.424	245	55	0.86	0.357

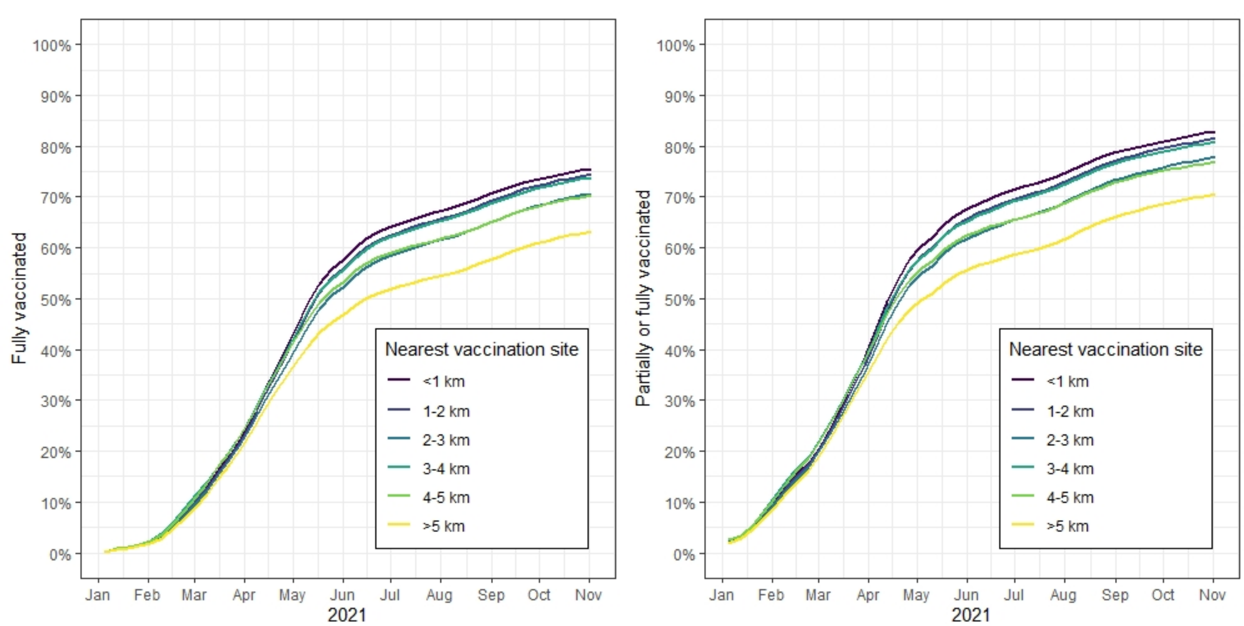
the average travel distance and Gini coefficient are relatively low (i.e., more equal), the optimal assignment under our proposed model would still open 218 dollar stores county-wide and maintain 333 existing vaccination sites, generating more uniform travel requirements and further reducing disparities across all tracts.

We observe slightly different results in Philadelphia and Los Angeles. Although average travel costs still decrease with the availability of dollar stores, the current vaccination sites are more geographically dispersed, resulting in modest reductions in distance travelled, particularly in the neighborhoods of south Los Angeles (e.g., Compton) and west Philadelphia. Nevertheless, across all seven metro areas—home to more than 36 million people or nearly 10% of the U.S. population—replacing existing pharmacy stores with optimally chosen dollar stores greatly reduces the average required travel distance to obtain a COVID vaccine, while simultaneously improving disparities, as measured by the sizeable drop in Gini coefficients (Table 1).

6. Vaccination Uptake

In selecting our earlier objective function—minimizing the average travel distance between geographic tracts and vaccination sites—we intuitively expect increasing barriers to vaccination access through greater travel distance is correlated with reduced vaccination rates. Utilizing both cross-sectional and panel data on vaccination rates by zip-code, we empirically examine the relationship between average travel distance and vaccination uptake.

Figure 8 **Average COVID vaccination rates at zip-code level in California.**



(a) Fully vaccinated

(b) Partially or fully vaccinated

We focus our analysis on California, given the state's wide variability in both vaccination rates and average travel distance to vaccination sites. As of June 1, 2021, for instance, full vaccination rates averaged 50% across the state's 1,764 zip-codes, but varied from 37% (bottom quartile) to 65% (top quartile), a vaccination gap that persisted through November 2021. Distance to the nearest pharmacy-based COVID vaccination site averaged 10.2 km across all zip-codes, but also widely varied from 1.1 km (bottom quartile) to 14.8 km (top quartile), reaching a maximum of 98.9 km. Figure 8 depicts the widening gap in vaccination rates among residents who live further from a vaccination site, particularly those living more than 5 km from a site.

6.1. Data Sources

Weekly vaccination data, by zip-code, are from the California Department of Public Health (2021). Demographic data are from the U.S. Census 2019 American Community Survey (US Census Bureau 2019). The state's existing 4,035 COVID vaccination sites at pharmacy-partners were scraped from `https://www.vaccines.gov/`. Locations and opening and closing dates of all mass vaccination sites, known as super points of dispensing (PODs), were hand-collected using Google News searches (Appendix Table A5).

6.2. Cross-Sectional Analysis

Using cross-sectional data on vaccination rates, by zip-code, we estimate to what extent closer proximity to retail pharmacies offering COVID vaccinations correlates with higher vaccination rates, under the following specifications:

$$FullyVaccinated_i = \beta_0 + \beta_1 LogDistanceNearestSite_i + \boldsymbol{\delta}\mathbf{X}_i + \varepsilon_i \tag{3}$$

$$PartiallyVaccinated_i = \beta_0 + \beta_1 LogDistanceNearestSite_i + \boldsymbol{\delta}\mathbf{X}_i + \varepsilon_i \tag{4}$$

The outcome variables, $FullyVaccinated_i$ or $PartiallyVaccinated_i$, are the proportion of the population aged 12 and older in zip-code i who are fully vaccinated or at least partially vaccinated, respectively, as of June 1, 2021. Our main variable of interest, $LogDistanceNearestSite_i$, is the natural-log distance from the geographic centroid of zip-code i to the nearest pharmacy vaccination site. The vector $\mathbf{X}_i$ includes demographic control variables at the zip-code level: population distribution by race (White, Black, Asian, Hispanic, other); health insurance status (employer-provided, Medicare, Medicaid, other, none); proportion of residents with a college degree; poverty level; unemployment rate; median household income ($000s); median home value ($000s); and population density (persons per square-mile).

Table 2, column (1) shows the unadjusted coefficient estimate of -0.0532 ($p < 0.001$), indicating that a 10% increase in travel distance corresponds to a 0.5 percentage-point decrease in full vaccination rates. After controlling for key demographics including, importantly, population density—a

Table 2 Predictors of vaccination rates as of June 1, 2021 at the zip-code level in California.

	Dependent variable:					
	Fraction Fully Vaccinated			Fraction Partially or Fully Vaccinated		
	(1)	(2)	(3)	(4)	(5)	(6)
Log-Distance to Nearest Site	-0.0532^{***}	-0.0470^{***}	-0.0252^{***}	-0.0612^{***}	-0.0511^{***}	-0.0271^{***}
	(0.0032)	(0.0037)	(0.0042)	(0.0034)	(0.0039)	(0.0044)
Race White		0.2326^{***}	-0.0139		0.2821^{***}	0.0018
		(0.0366)	(0.0458)		(0.0390)	(0.0485)
Race Black		-0.2541^{**}	-0.2100^{**}		-0.2070^{*}	-0.1763^{*}
		(0.0806)	(0.0781)		(0.0858)	(0.0827)
Race Asian		0.5622^{***}	0.1608^{**}		0.6697^{***}	0.2084^{**}
		(0.0529)	(0.0611)		(0.0563)	(0.0647)
Race Hispanic		0.1038^{**}	0.0756		0.1963^{***}	0.1350^{**}
		(0.0371)	(0.0439)		(0.0395)	(0.0465)
Health Insurance Employer			0.0743			0.0848
			(0.0482)			(0.0510)
Health Insurance Medicare			0.1769^{**}			0.1730^{**}
			(0.0572)			(0.0606)
Health Insurance Medicaid			0.0196			0.0640
			(0.0556)			(0.0589)
Health Insurance Other			-0.1592^{**}			-0.1370^{*}
			(0.0608)			(0.0643)
College Graduate			0.2715^{***}			0.2695^{***}
			(0.0384)			(0.0406)
Poverty Level			0.1196^{*}			0.1582^{**}
			(0.0512)			(0.0542)
Unemployment Rate			-0.2168^{**}			-0.2417^{**}
			(0.0766)			(0.0810)
Median Household Income ($000s)			0.0002			0.0005^{*}
			(0.0002)			(0.0002)
Median Home Value ($000s)			0.0001^{***}			0.0002^{***}
			(0.00002)			(0.00002)
Population Density			-0.000004^{***}			-0.000004^{***}
			(0.000001)			(0.000001)
Constant	0.5747^{***}	0.3746^{***}	0.3231^{***}	0.6661^{***}	0.3962^{***}	0.3324^{***}
	(0.0066)	(0.0344)	(0.0326)	(0.0070)	(0.0366)	(0.0345)
Observations	1,764	1,764	1,764	1,764	1,764	1,764
R^2	0.134	0.227	0.379	0.154	0.241	0.398

Significance levels: *p<0.05; **p<0.01; ***p<0.001

strong proxy for urban or rural locations—the estimate attenuates to -0.0252 ($p < 0.001$), corresponding to a 0.2 percentage-point decrease in full vaccination rates per 10% increase in travel distance. Columns (2) and (3) clearly highlight the racial disparities in vaccination rates, with nearly a 37 percentage-point gap between Asian and Black residents of California, after controlling for health insurance, income, and other key factors. Examining partial vaccination rates finds qualitatively similar results, as shown in columns (4)-(6).

To check the robustness of our earlier specification, we first examine whether the number of pharmacy vaccination sites within a particular radius is correlated with vaccination uptake:

$$FullyVaccinated_i = \beta_0 + \beta_1 VaccinationSites_i + \boldsymbol{\delta}\mathbf{X}_i + \varepsilon_i \tag{5}$$

where $VaccinationSites_i$ is the number of pharmacy vaccination sites within a radius (1 km, 2 km, 5 km, or 10 km) of zip-code i. Results indicate that each additional vaccination site within a 1 km radius corresponds to 1.6 percentage-point increase in full vaccination rates, as shown in Appendix Table A2, column (1). As the radius grows, the coefficient estimate decreases, as expected. Under either full vaccination or partial vaccination rates, the number of potential nearby locations to obtain a vaccination is positively correlated with uptake. Finally, we repeat our cross-sectional analysis for six time periods, from June 1, 2021 to November 2, 2021. Our results are quite consistent, and we confirm the baseline increase in full vaccination (Appendix Table A3) and partial vaccination (Appendix Table A4) rates over time, as indicated by the constant term.

6.3. Time-Series Analysis

Despite strong correlational evidence demonstrating a link between travel distance to vaccination sites and uptake, one may question whether increasing vaccination access *causally* increases vaccination uptake. To further examine this potential causal relationship, we conduct a time-series analysis, identifying off variation in the openings and closures of super PODs in California between January and June 2021 (Appendix Table A5). We assume the following time-series specification:

$$NewlyVaccinated_{it} = \beta_0 + \beta_1 LogDistanceNearestPod_{it} + \alpha_i + \omega_t + \varepsilon_{it} \tag{6}$$

where $NewlyVaccinated_{it}$ is the number of individuals in zip-code i who are newly vaccinated during week t. The variable $LogDistanceNearestPod_{it}$ is the natural-log distance from the geographic centroid of zip-code i to the nearest super POD that is open during week t. We include two-way fixed effects for zip-code i (α_i) and week t (ω_t).

As with the cross-sectional analysis, we also consider an alternative variable measuring the number of super PODs within a specified radius of each zip-code. Given their geographic sparsity—only 25 super PODs were opened across the entire state compared to more than 4,000 pharmacy vaccination sites—we expand the radius to include sites within 100 km.

$$NewlyVaccinated_{it} = \beta_0 + \beta_1 OpenSuperPods_{it} + \alpha_i + \omega_t + \varepsilon_{it} \tag{7}$$

where $OpenSuperPods_{it}$ is the number of super PODs within a radius (10 km, 20 km, 50 km, 100 km) of zip-code i and open during week t.

Table 3 **Time series regressions of new weekly COVID vaccinations at the zip-code level in California.**

	Dependent variable: Newly Vaccinated Persons per Week				
	(1)	(2)	(3)	(4)	(5)
Log-Distance to Nearest Open Super POD	-38.548^{***} (7.870)				
Super PODs Open < 10 km		187.035^{***} (21.845)			
Super PODs Open < 20 km			123.534^{***} (10.973)		
Super PODs Open < 50 km				72.157^{***} (4.233)	
Super PODs Open < 100 km					54.735^{***} (2.936)
Fixed Effects	Zip Code, Week	Zip Code, Week	Zip Code, Week	Zip Code, Week	Zip Code, Week
Observations	37,044	37,044	37,044	37,044	37,044
R^2	0.003	0.013	0.021	0.044	0.046

Observations are at the week-zip-code level, between January 12, 2021 and June 1, 2021. Super points of dispensing (PODs) refer to mass vaccination sites, such as Disneyland. Standard errors are reported in parentheses and clustered at the zip-code level. Significance levels: *p<0.05; **p<0.01; ***p<0.001

Table 3, column (1) shows a coefficient estimate of -38.548 ($p < 0.001$), suggesting that a 10% increase in travel distance to a super POD vaccination site results in 3.8 fewer vaccinated individuals in every zip-code and every week. Perhaps more intuitively, column (2) shows that each additional super POD that is operational and within a 10 km radius causally increases weekly vaccinations per zip-code by 187—a 33% gain from the 565 vaccinations completed, on average, per zip-code per week between January and June 2021. Across California, seventeen zip-codes are within 10 km of each super POD, on average, amounting to more than 3,000 additional vaccinations per open POD every week. Larger PODs in more densely populated regions would naturally provide more vaccinations (e.g., Dodger Stadium is located within 10 km of 45 unique zip-codes and had peak capacity of 12,000 vaccinations per day). As expected, the marginal benefits of adding super PODs diminishes as the radius increases, shown by the decreasing coefficients in Table 3 columns (3)-(5), as residents would need to travel significantly greater distances to reach a site.

While we focus on the period of January to June 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 June 1, 2021 as most 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 both population size differences across zip-codes, as well as other potentially confounding variables such as population density, public transportation access, and resident political leanings. Together with the cross-sectional analysis for all pharmacy-based COVID vaccination sites in California, the time-series analysis provides compelling evidence demonstrating that reducing travel distance to vaccination sites can boost vaccination uptake, supporting our choice of objective function in the earlier optimal facility location model.

7. Discussion

This paper presents a simple and interpretable mixed-integer programming model that optimally selects vaccination locations among current pharmacy partner sites along with dollar stores, and demonstrates the considerable benefits of including alternative retailers in vaccine distribution channels. To maintain computational tractability, we decompose the national vaccination location problem into state-level separable sub-problems. Our objective minimizes average population-weighted travel distance between home census tracts and the assigned vaccination site(s), subject to vaccine supply and location budget constraints. Numerical results suggest that adding dollar stores can potentially yield significant benefits, reducing travel distance and alleviating racial and geographic disparities in vaccine access. Remarkably, the average travel distance nationwide drops from 6.2km to 2.4km—without increasing the total number of vaccination locations in operation—while providing proximity benefits especially for Hispanic and Black Americans. In contrast to most operational settings where a trade-off between equity and efficiency typically exists, we find a surprisingly large improvement in both equity (measured by Gini coefficient) and efficiency (measured by travel cost) in almost every state. Our detailed case study of several populous U.S. counties illustrates that racially diverse areas can especially benefit from replacing some redundant locations with dollar stores in more underserved communities. Sensitivity analysis indicates that opening either too few or too many stores generates high travel costs for various reasons, assuming a fixed supply of vaccines. We find, however, that consolidation of locations is doable without significantly increasing travel costs. Lastly, our cross-sectional and time-series analysis for California shows that vaccination uptake is inversely correlated with travel distance required for vaccination, highlighting the importance of smart vaccination location selection. While our work specifically examines partnering with dollar stores, the model is generalizable and could be readily applied to other retailers (e.g., gas stations, post offices).

With the current abundance of COVID-19 vaccines in the United States—and a highly decentralized vaccination campaign—how best to distribute inoculations to ensure equitable vaccine access is a pressing concern. Replacing some existing locations in vaccination-saturated regions (e.g., dense urban areas, higher-income communities) with dollar stores in underserved communities (e.g., rural areas, lower-income communities) will lead to better access and greater racial equity. Newly added dollar stores not only reduce the travel cost for residents by directly providing closer vaccination sites, but they also provide indirect benefits. Existing sites are geographically imbalanced in the sense that some regions with large populations have only a few (or none) nearby vaccination sites. As a result, these individuals commute to adjacent tracts for vaccination, potentially taking limited slots away from local residents, given the limited capacity of each single site. This forces local residents who might originally live close to a vaccination site to travel further—or potentially skip vaccination altogether—creating a domino effect where eventually everyone experiences a greater travel cost regardless of how many vaccination sites are nearby. Documented by news media nationwide (CNN 2021, NPR 2021), this vaccine cannibalization further propagates disparities, particularly as the extra time spent scheduling or traveling to an appointment creates an undue burden on lower income and vulnerable populations. Of note, in areas that are neither supply saturated nor unsaturated (e.g., suburban areas), the actual implementation might vary, as dollar stores are still useful but we begin to see diminishing marginal returns from their addition. Thus, it may not be feasible nor cost-effective to open a new vaccination site (and close an existing one). We expect similar outcomes with partnering with other retain chains that share characteristics with dollar stores, such as locating in underserved communities.

7.1. Limitations and Future Work

Our model has several limitations that could be explored in future research. Our numerical study is conducted at a census tract-level and uses Euclidean distances between population centroids and vaccination sites, ignoring geospatial heterogeneity within a tract. Vaccination data at a higher degree of granularity, if available, would enable us to more accurately measure disparities by race and other metrics (e.g., income, age, education, political affiliation, etc.). Similarly, our empirical analysis relies on zip-code level vaccination data and the locations of mass vaccination centers in California, given the lack of consistent and complete time-series vaccination data across states. Ideally, a full time-series analysis on all vaccination locations nationwide would help us better estimate the causal effect of vaccination access on uptake, which could possibly bring up new insights, implications, and future research questions.

In terms of our modeling approach, our optimization model minimizes the average travel cost and ignores other objectives (e.g., cases of infection and death, operating costs) that might be of interest to decision-makers during a pandemic. To achieve tractability, we make simplifying assumptions and ignore heterogeneities in per-store vaccination capacity, vaccination rates across different areas and subgroups, number of doses required (single-dose vs. double-dose), and storage conditions by vaccine type. In addition, our model could be extended 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 unvaccinated population size. These extensions would be of practical use given the current shortage of healthcare workers and other resources needed for the widespread delivery of booster doses. Another future direction is to examine behavioral aspects of vaccination (e.g., vaccine hesitancy among different subgroups), which has been identified as a major obstacle to achieving herd immunity (Benito 2021, Taylor 2021).

7.2. Conclusions

This paper highlights the critical role of dollar stores (and potentially other retail chains) in reducing the required travel distance to obtain a COVID-19 vaccination, while simultaneously alleviating racial and geographic disparities in vaccine access. Our study offers an interpretable, quantitative framework that can provide federal and state health departments with guidance on optimally selecting vaccination sites to improve vaccination access against a seasonal epidemic or an endemic disease—a likely outcome for COVID.

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Appendix A: Tables

Table A1 Results of optimal COVID vaccination facility locations for each state.

				Current Locations				Optimal Locations				
State	Population	% Urban	Tracts	Pharmacy Stores	Dollar Stores	Mean Dist. (km)	Gini Coeff.	Pharmacy Stores	Dollar Stores	Mean Dist. (km)	Gini Coeff.	Demand at Dollar Stores
Alabama	4,779,736	59.0%	1,181	1,184	0	8.6	0.598	444	740	2.7	0.436	62.9%
Arizona	6,364,323	89.8%	1,526	959	0	7.2	0.760	640	319	3.5	0.684	32.9%
Arkansas	2,915,918	56.2%	686	696	0	15.7	0.654	274	422	3.3	0.498	61.1%
California	37,253,956	95.0%	8,057	4,035	0	2.4	0.536	3,227	808	1.8	0.496	19.6%
Colorado	5,029,196	86.2%	1,249	622	0	4.4	0.668	413	209	2.4	0.541	30.3%
Connecticut	3,574,097	88.0%	833	781	0	3.8	0.524	606	175	2.2	0.459	22.3%
Delaware	897,934	83.3%	218	445	0	2.6	0.448	336	109	2.0	0.425	24.5%
Dist. of Columbia	601,723	100.0%	179	232	0	0.9	0.412	226	6	0.9	0.400	3.1%
Florida	18,801,310	91.2%	4,245	3,228	0	3.0	0.487	1,935	1,293	1.8	0.412	39.9%
Georgia	9,687,653	75.1%	1,969	1,530	0	6.4	0.562	593	937	2.3	0.397	57.9%
Idaho	1,567,582	70.6%	298	292	0	7.3	0.666	216	76	4.5	0.603	25.6%
Illinois	12,830,632	88.4%	3,123	2,528	0	14.0	0.741	1,573	955	1.8	0.504	36.6%
Indiana	6,483,802	72.4%	1,511	1,305	0	9.1	0.634	621	684	2.4	0.488	52.2%
Iowa	3,046,355	64.0%	825	720	0	11.4	0.659	429	291	3.6	0.563	40.0%
Kansas	2,853,118	74.2%	770	751	0	14.3	0.706	484	267	2.8	0.544	36.3%
Kentucky	4,339,367	58.4%	1,115	1,295	0	8.3	0.592	684	611	2.6	0.464	48.5%
Louisiana	4,533,372	73.2%	1,148	2,491	0	5.1	0.552	1,642	849	2.6	0.498	36.3%
Maine	1,328,361	38.7%	358	238	0	6.7	0.555	135	103	4.8	0.542	43.5%
Maryland	5,773,552	87.2%	1,406	1,039	0	4.6	0.543	729	310	2.1	0.468	29.2%
Massachusetts	6,547,629	92.0%	1,478	1,224	0	4.2	0.559	962	262	2.1	0.478	20.9%
Michigan	9,883,640	74.6%	2,813	1,760	0	4.2	0.576	955	805	2.3	0.502	45.1%
Minnesota	5,303,925	73.3%	1,338	720	0	7.5	0.600	470	250	4.1	0.568	32.4%
Mississippi	2,967,297	49.4%	664	543	0	10.9	0.562	126	417	3.7	0.476	76.9%
Missouri	5,988,927	70.4%	1,393	1,050	0	15.5	0.719	486	564	2.9	0.528	53.4%
Montana	989,415	55.9%	271	173	0	13.1	0.699	139	34	9.0	0.669	18.9%
Nebraska	1,826,341	73.1%	532	288	0	19.7	0.712	139	149	3.9	0.644	48.2%
Nevada	2,700,551	94.2%	687	397	0	7.3	0.789	280	117	2.2	0.576	29.4%
New Hampshire	1,316,470	60.3%	295	330	0	7.3	0.525	240	90	3.8	0.483	27.7%
New Jersey	8,791,894	94.7%	2,010	1,569	0	1.9	0.450	1,188	381	1.4	0.444	23.8%
New Mexico	2,059,179	77.4%	499	228	0	14.7	0.760	80	148	4.2	0.626	61.9%
New York	19,320,388	87.9%	4,919	2,957	0	3.8	0.628	2,074	883	1.5	0.546	27.3%
North Carolina	9,535,483	66.1%	2,195	1,611	0	6.8	0.554	623	988	2.7	0.429	60.4%
North Dakota	672,591	59.9%	205	417	0	11.5	0.698	341	76	5.9	0.670	18.1%
Ohio	11,536,504	77.9%	2,952	3,989	0	4.4	0.575	2,629	1,360	2.1	0.490	35.5%
Oklahoma	3,751,351	66.2%	1,046	703	0	7.1	0.615	272	431	2.7	0.518	58.5%
Oregon	3,831,074	81.0%	834	499	0	5.4	0.638	368	131	3.2	0.582	25.3%
Pennsylvania	12,702,379	78.7%	3,218	3,091	0	3.7	0.550	2,060	1,031	2.0	0.490	33.6%
Rhode Island	1,052,567	90.7%	244	283	0	2.0	0.485	204	79	1.7	0.515	29.4%
South Carolina	4,625,364	66.3%	1,103	1,081	0	8.6	0.617	440	641	2.6	0.432	60.2%
South Dakota	800,594	56.7%	222	199	0	57.2	0.714	109	90	6.7	0.657	45.5%
Tennessee	6,346,105	66.4%	1,497	2,094	0	8.4	0.634	1,168	926	2.5	0.411	45.7%
Texas	25,145,561	84.7%	5,265	3,673	0	5.5	0.668	1,668	2,005	1.9	0.462	52.0%
Utah	2,763,885	90.6%	588	438	0	3.3	0.570	332	106	2.3	0.542	23.8%
Vermont	625,741	38.9%	184	237	0	7.6	0.568	182	55	5.3	0.544	25.6%
Virginia	7,994,802	75.5%	1,907	1,743	0	6.2	0.594	1,128	615	2.5	0.485	34.4%
Washington	6,724,540	84.1%	1,458	1,073	0	4.2	0.584	938	135	3.5	0.576	12.9%
West Virginia	1,852,994	48.7%	484	627	0	9.9	0.588	323	304	3.8	0.466	51.5%
Wisconsin	5,686,986	70.2%	1,409	1,015	0	6.7	0.613	661	354	3.3	0.562	34.4%
Wyoming	563,626	64.8%	132	102	0	17.8	0.729	65	37	6.5	0.671	36.7%
U.S. Total	306,569,790	80.7%	72,539	58,485	0	6.2	0.597	35,857	22,628	2.4	0.495	37.5%

Table A2 Predictors of vaccination rates as of June 1, 2021 at the zip-code level in California.

	Dependent variable:							
	Fraction Fully Vaccinated				Fraction Partially or Fully Vaccinated			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vaccination Sites <1 km	0.0163***				0.0163***			
	(0.0039)				(0.0041)			
Vaccination Sites <2 km		0.0071***				0.0074***		
		(0.0016)				(0.0017)		
Vaccination Sites <5 km			0.0026***				0.0028***	
			(0.0004)				(0.0005)	
Vaccination Sites <10 km				0.0010***				0.0011***
				(0.0002)				(0.0002)
Race White	0.2298***	0.2289***	0.2362***	0.2388***	0.2781***	0.2776***	0.2856***	0.2888***
	(0.0382)	(0.0381)	(0.0380)	(0.0379)	(0.0408)	(0.0407)	(0.0405)	(0.0405)
Race Black	−0.0796	−0.1038	−0.1512	−0.1954*	−0.0166	−0.0423	−0.0934	−0.1433
	(0.0825)	(0.0828)	(0.0831)	(0.0840)	(0.0881)	(0.0883)	(0.0886)	(0.0896)
Race Asian	0.7836***	0.7603***	0.7216***	0.7051***	0.9136***	0.8874***	0.8453***	0.8249***
	(0.0516)	(0.0526)	(0.0531)	(0.0534)	(0.0551)	(0.0561)	(0.0567)	(0.0569)
Race Hispanic	0.1556***	0.1507***	0.1467***	0.1378***	0.2520***	0.2472***	0.2429***	0.2332***
	(0.0385)	(0.0384)	(0.0382)	(0.0382)	(0.0411)	(0.0410)	(0.0408)	(0.0407)
Constant	0.2618***	0.2626***	0.2548***	0.2531***	0.2747***	0.2749***	0.2664***	0.2641***
	(0.0349)	(0.0349)	(0.0348)	(0.0347)	(0.0373)	(0.0372)	(0.0371)	(0.0370)
Observations	1,764	1,764	1,764	1,764	1,764	1,764	1,764	1,764
R^2	0.163	0.164	0.172	0.176	0.175	0.176	0.184	0.188

Significance levels: *p<0.05; **p<0.01; ***p<0.001

Table A3 Predictors of full vaccination rates at various dates at the zip-code level in California.

	Dependent variable: Fraction Fully Vaccinated					
	1-Jun-21	6-Jul-21	3-Aug-21	7-Sep-21	5-Oct-21	2-Nov-21
Log-Distance to Nearest Site	−0.0470***	−0.0497***	−0.0523***	−0.0509***	−0.0517***	−0.0546***
	(0.0037)	(0.0039)	(0.0039)	(0.0039)	(0.0040)	(0.0040)
Race White	0.2326***	0.2482***	0.2246***	0.2539***	0.2295***	0.2302***
	(0.0366)	(0.0388)	(0.0389)	(0.0388)	(0.0396)	(0.0400)
Race Black	−0.2541**	−0.2019*	−0.2460**	−0.1765*	−0.1591	−0.1465
	(0.0806)	(0.0852)	(0.0855)	(0.0853)	(0.0870)	(0.0878)
Race Asian	0.5622***	0.6874***	0.6694***	0.6691***	0.6575***	0.6520***
	(0.0529)	(0.0559)	(0.0561)	(0.0560)	(0.0571)	(0.0577)
Race Hispanic	0.1038**	0.1839***	0.1870***	0.2292***	0.2482***	0.2680***
	(0.0371)	(0.0393)	(0.0394)	(0.0393)	(0.0401)	(0.0405)
Constant	0.3746***	0.3808***	0.4195***	0.4263***	0.4539***	0.4651***
	(0.0344)	(0.0364)	(0.0365)	(0.0364)	(0.0371)	(0.0375)
Observations	1,764	1,764	1,764	1,764	1,764	1,764
R^2	0.227	0.248	0.256	0.246	0.246	0.255

Significance levels: *p<0.05; **p<0.01; ***p<0.001

Table A4 **Predictors of full or partial vaccination rates at various dates at the zip-code level in California.**

	Dependent variable: Fraction Partially or Fully Vaccinated					
	1-Jun-21	6-Jul-21	3-Aug-21	7-Sep-21	5-Oct-21	2-Nov-21
Log-Distance to Nearest Site	-0.0511^{***}	-0.0512^{***}	-0.0541^{***}	-0.0513^{***}	-0.0526^{***}	-0.0559^{***}
	(0.0039)	(0.0041)	(0.0041)	(0.0040)	(0.0041)	(0.0042)
Race White	0.2821^{***}	0.2775^{***}	0.2592^{***}	0.2884^{***}	0.2607^{***}	0.2607^{***}
	(0.0390)	(0.0405)	(0.0407)	(0.0402)	(0.0411)	(0.0415)
Race Black	-0.2070^{*}	-0.1535	-0.1862^{*}	-0.0989	-0.0858	-0.0718
	(0.0858)	(0.0890)	(0.0894)	(0.0884)	(0.0903)	(0.0912)
Race Asian	0.6697^{***}	0.7356^{***}	0.7076^{***}	0.6952^{***}	0.6796^{***}	0.6729^{***}
	(0.0563)	(0.0584)	(0.0587)	(0.0580)	(0.0593)	(0.0599)
Race Hispanic	0.1963^{***}	0.2598^{***}	0.2740^{***}	0.3235^{***}	0.3304^{***}	0.3457^{***}
	(0.0395)	(0.0410)	(0.0412)	(0.0407)	(0.0416)	(0.0420)
Constant	0.3962^{***}	0.3981^{***}	0.4363^{***}	0.4448^{***}	0.4724^{***}	0.4841^{***}
	(0.0366)	(0.0380)	(0.0382)	(0.0377)	(0.0386)	(0.0389)
Observations	1,764	1,764	1,764	1,764	1,764	1,764
R^2	0.241	0.248	0.255	0.243	0.245	0.256

Significance levels: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table A5 **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
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

Appendix B: Figures

Figure B1 **Percentage demand covered by dollar stores vs. change in Gini coefficient under the optimal solution.**

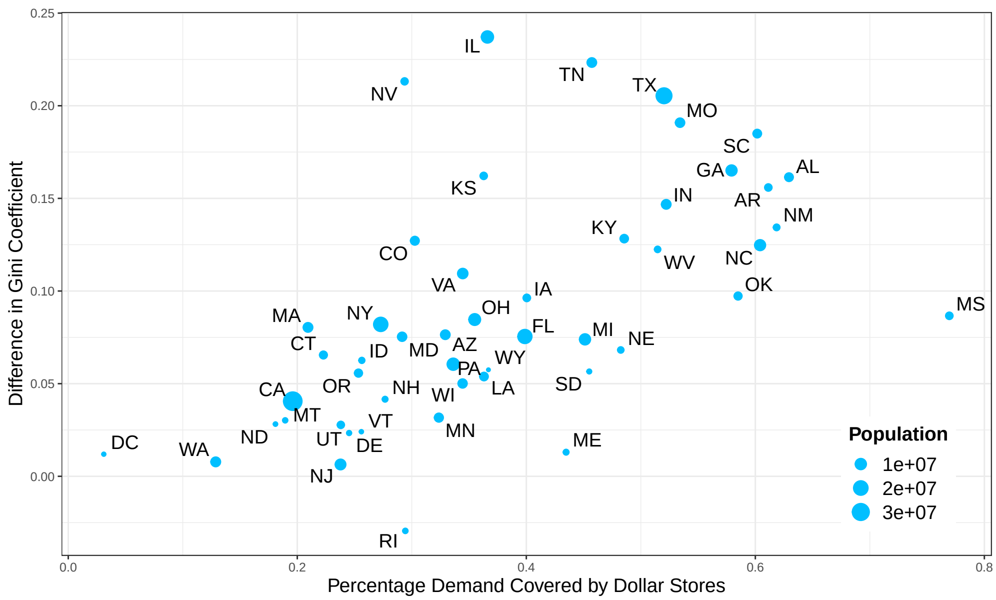


Figure B2 **Racial distribution of residents in Cook County, Illinois (Cable 2013).**

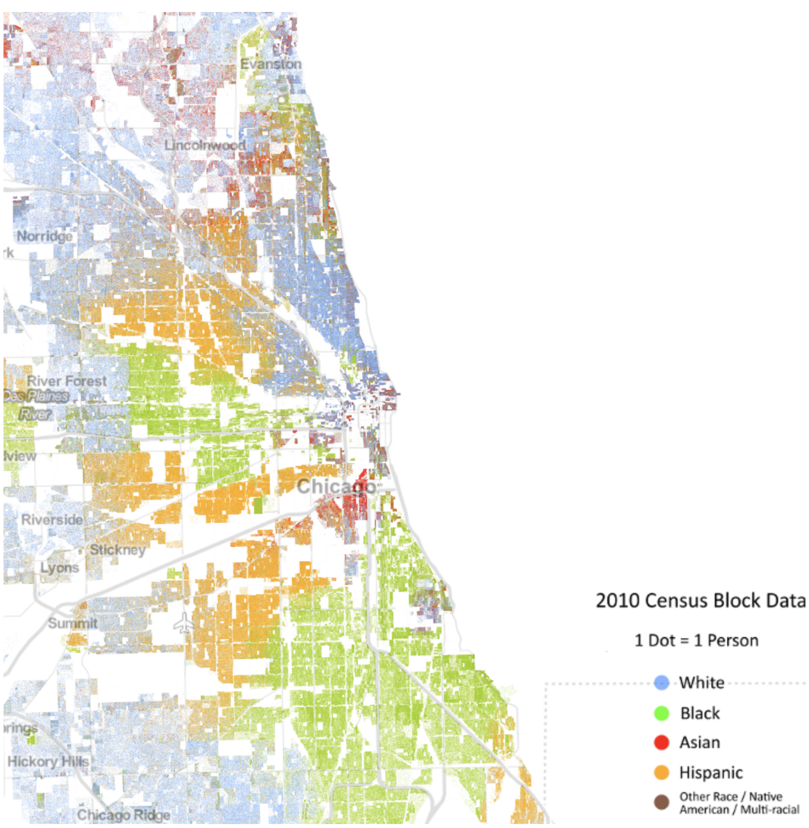
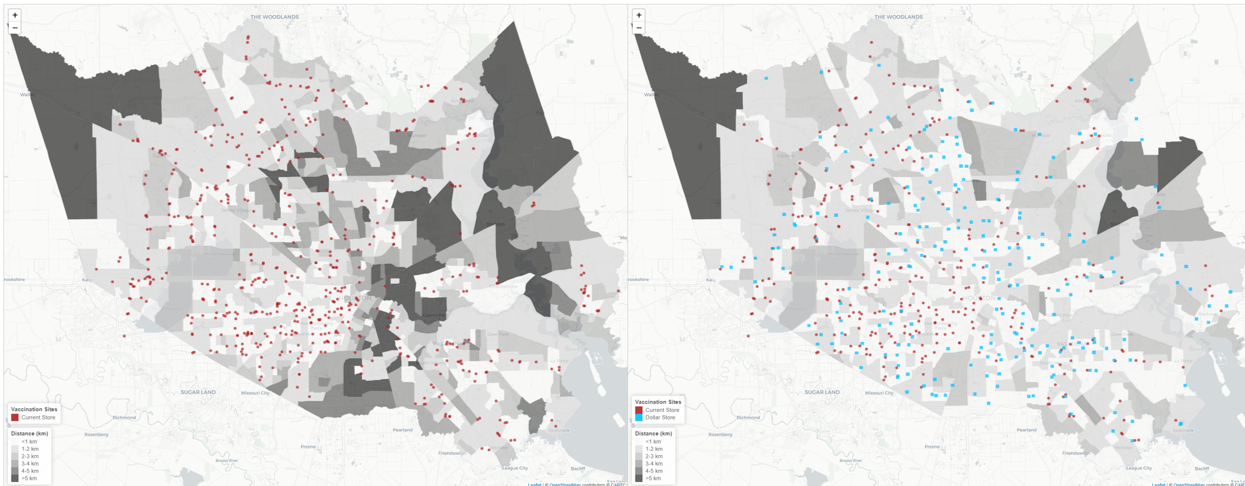
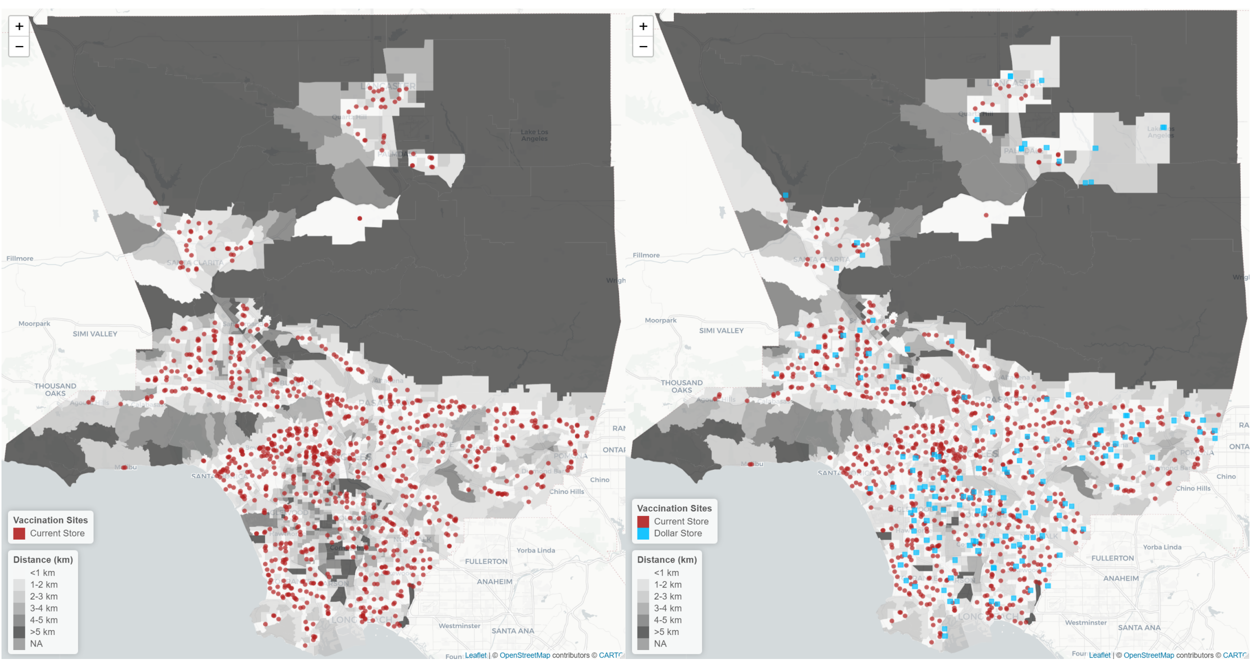


Figure B3 **COVID vaccination sites and average travel distance by tract in Harris County, Texas.**



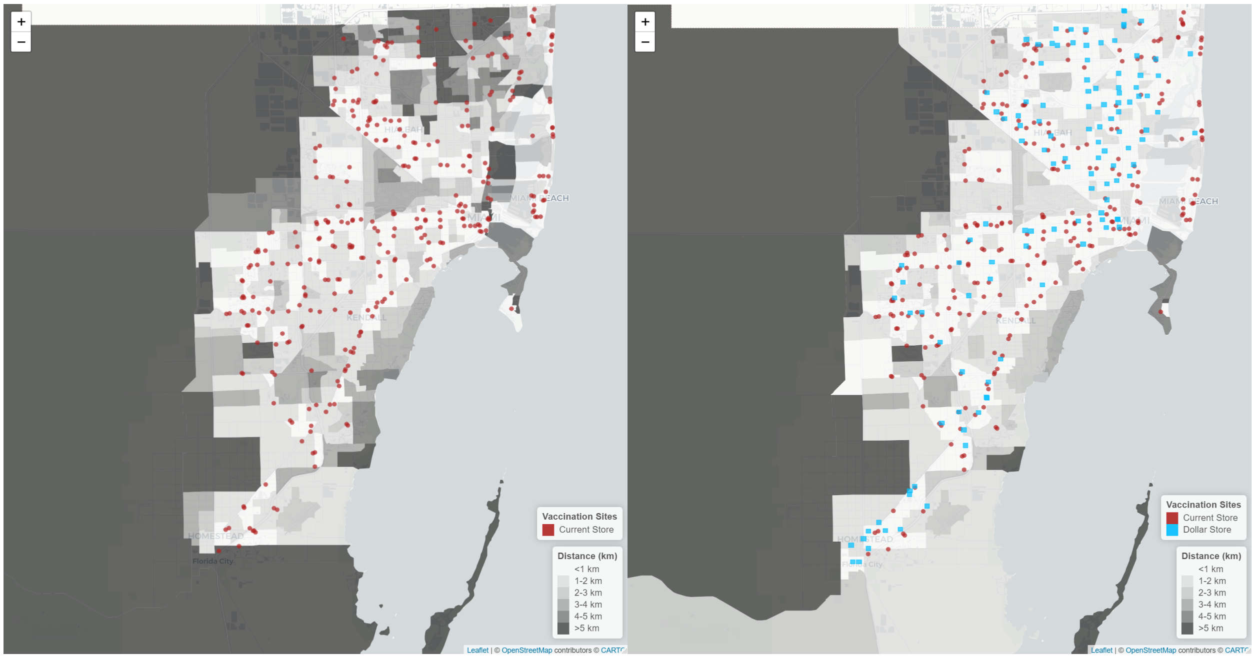
(a) Current locations (b) Optimal locations including dollar stores

Figure B4 **COVID vaccination sites and average travel distance by tract in Los Angeles County, California.**



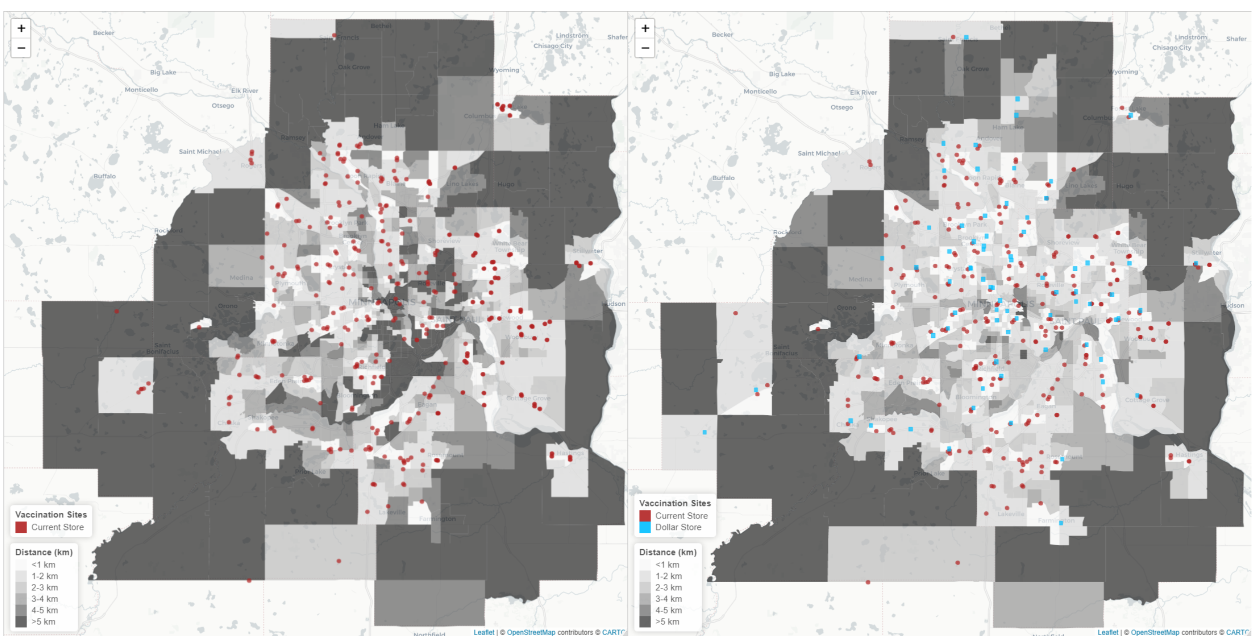
(a) Current locations (b) Optimal locations including dollar stores

Figure B5 **COVID vaccination sites and average travel distance by tract in Miami-Dade County, Florida.**



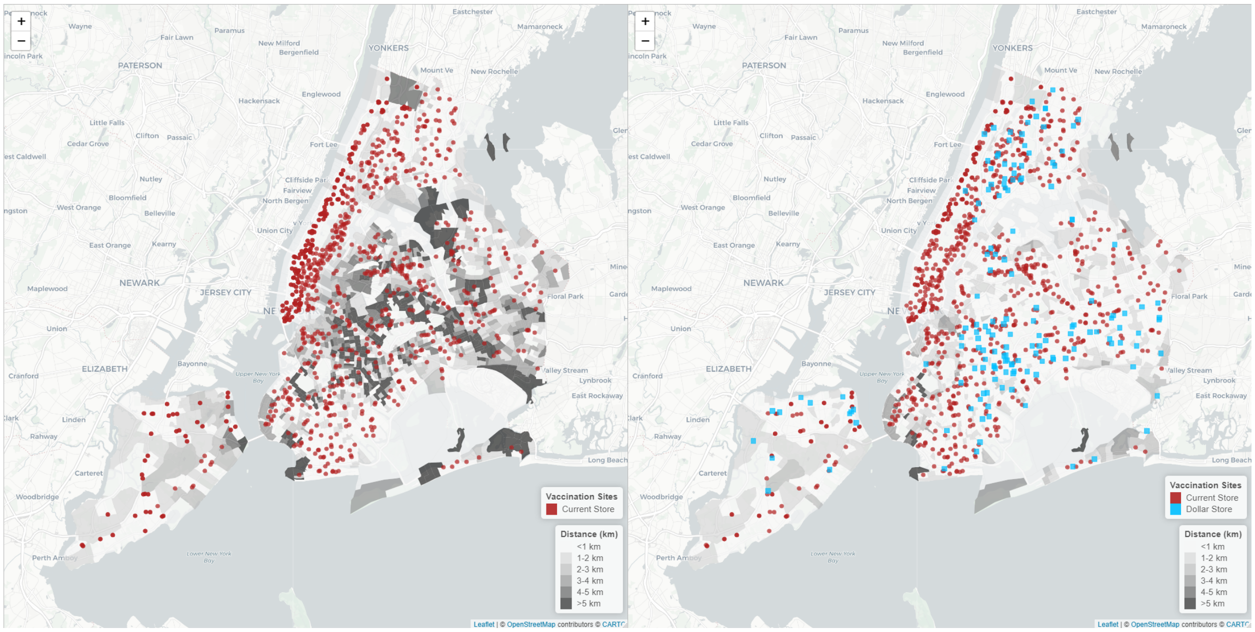
(a) Current locations (b) Optimal locations including dollar stores

Figure B6 **COVID vaccination sites and average travel distance by tract in Minneapolis-Saint Paul metro area, Minnesota.**



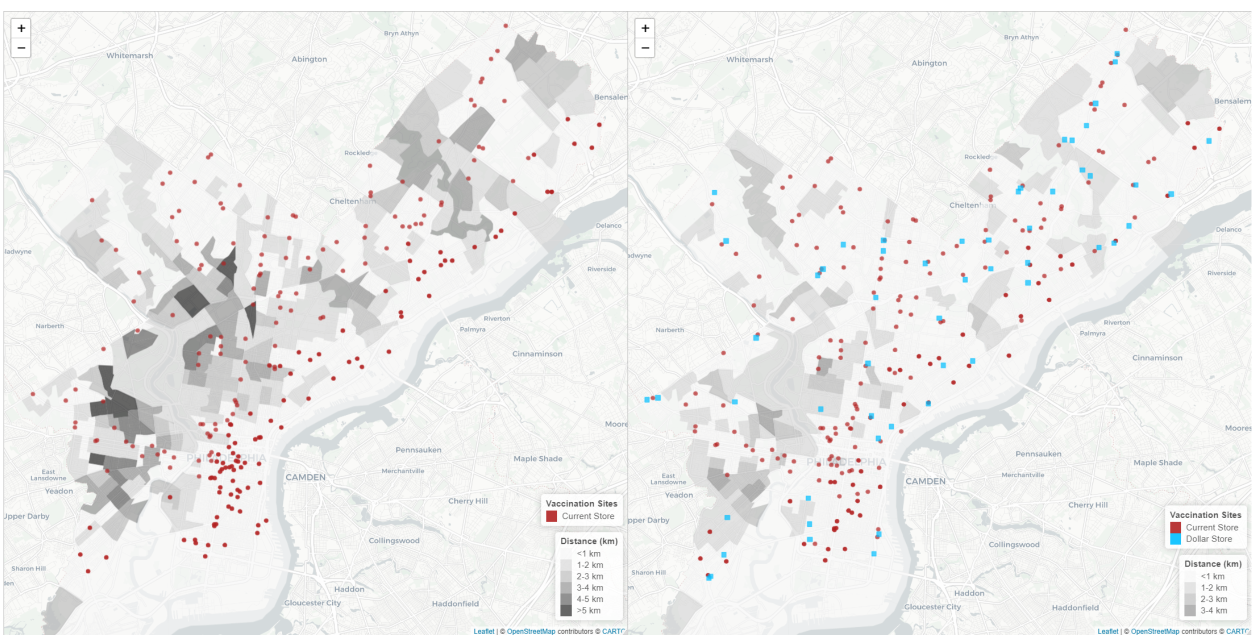
(a) Current locations (b) Optimal locations including dollar stores

Figure B7 COVID vaccination sites and average travel distance by tract in New York City metro area, New York.



(a) Current locations (b) Optimal locations including dollar stores

Figure B8 COVID vaccination sites and average travel distance by tract in Philadelphia County, Pennsylvania.



(a) Current locations (b) Optimal locations including dollar stores