# How to Stop Contagion: Applying Network Science to Evaluate the Effectiveness of Covid-19 Vaccine Distribution Plans*

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**Abstract**

President Trump's haphazard decision to delegate Covid-19 vaccine distribution to US states set up conditions for evaluating state-level vaccine prioritization policies using a quasi-experimental design. Despite agreement on the goal, state-formulated vaccine distribution plans diverged beyond initial priority groups: some prioritized based on mortality risks only (i.e., age), while others also included several high-exposure risk groups. After establishing that this divergence was driven by stochastic rather than systematic factors, I leverage it as an identification strategy to test a key insight from network theory: reducing contagion requires disabling the transmission potential of the most connected actors. Based on this, I argue that early prioritization of high-exposure risk groups, especially public-facing essential workers, led to a greater reduction in Covid-19 cases than prioritization based solely on mortality risks. Analysis of daily Covid-19 data in a matched sample of Oregon and California counties shows strong support for this hypothesis.

*Replication files are available in the JOP Dataverse (https://dataverse.harvard.edu/dataverse/jop). The empirical analysis has been successfully replicated by the JOP replication analyst. Supplementary material for this article is available in the appendix in the online edition.

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The 2020 Covid-19 pandemic put public health policy-making under the microscope of public scrutiny. Fueled by the anguish of social isolation brought about by closures and travel restrictions, the public poured over every aspect of each new policy, from economic impact, to fairness, to public safety. The combination of urgency and public outcry resulted in wild policy oscillation, with mask mandates, curfews, and quarantines implemented and lifted, often seemingly at random. Once vaccines became available, health authorities were faced with a yet more pressing policy decision on how to distribute the initially scarce vaccine supplies. In this article, I show how the policy-making processes around early vaccine distribution in the US led to a divergence in vaccine prioritization, resulting in substantial variation in public health outcomes.

Combined with President Trump's haphazard decision to delegate Covid-19 vaccine distribution to US states, these conditions set up a unique opportunity for evaluating alternative vaccine prioritization policies, as well as the general mechanisms of preventing contagion in social and political networks. Lacking experience and expertise in drafting and implementing new vaccine distribution protocols, states were largely unprepared for the task. Despite a general agreement that vaccine prioritization plans should be designed so as to minimize deaths and hospitalizations, public health officials lacked a clear understanding or consensus on the best way to achieve these goals. Rather broad guidelines from the Center for Disease Control (CDC) forced states to define vaccine priority groups using their own discretion. As a result, prioritization lists diverged as soon as vaccination campaigns moved beyond groups with the highest mortality risk.[1]

The broad strategy was to prioritize vaccine access based on vulnerability, proxied by age, from oldest to youngest.[2] Some US states, however, also prioritized one or more groups with the highest risk of exposure: K-12 educators and staff, incarcerated individuals, and agriculture and food employees. Thus, the primary difference among US states' vaccine priority approaches was in the relative place in the queue for these three groups.

[1]The most at-risk groups were defined as medical workers, the elderly, and those residing in congregated settings.

[2]In addition to age, some states also gave vaccine priority to individuals with specific pre-existing medical conditions.

While this divergence is apparent in hindsight, a combination of statistical and qualitative analyses reveals little evidence that it was either intentional or a result of systematic drivers, such as political interests. The results of these analyses suggest that, rather than customizing vaccine prioritization to their local political or demographic context, states simply did their best to adhere to the national guidelines, however vague. The analyses also suggest that variation in state-formulated priority lists was due to stochastic, rather than systematic factors, such as variation in interpreting the CDC guidelines, a failure to anticipate the pace of increases in vaccine supply, and idiosyncratic delays in state-level decision-making.

Based on these analyses, I argue that the divergence in state-formulated vaccine priority plans sets up conditions for testing a key network theory insight—that the bulk of transmission through a network is disproportionately channeled through only a handful of highly connected or *central* actors (Granovetter 1973; Padgett and Ansell 1993; Kirkland 2011; Box-Steffensmeier et al. 2018). In a service-oriented economy, such as the US, grocery store employees are the largest occupational group engaged in the highest number of face-to-face interactions. In contrast to other service sectors, grocery stores had to remain open throughout the pandemic, even when most other retail businesses and even schools reduced hours or switched to remote operation.[3] As such, grocery employees function as central nodes within a transmission network of a virus that diffuses most effectively among individuals in close contact in indoor spaces.

The handful of US states, which happened to assign grocery employees a higher priority in the vaccine eligibility queue, essentially reduced or disabled the virus transmission potential of the most central actors in the network of human interactions.[4] In contrast, states that gave lower priority to grocery employees, especially if they chose to prioritize based on age only, effectively allocated their vaccines to the most isolated actors within the network.[5] Individuals

[3]Though some grocers were able to limit exposure through offering pick-up and delivery services, most found these options unfeasible due to added costs, a lack of resources and experience with online platforms, or customer preference for in-store shopping.

[4]Though not available at the start of vaccine prioritization, evidence that Covid-19 vaccines prevent or substantially reduce transmission of the virus has since become available (Eyre et al. 2022; Harris et al. 2021; Shah et al. 2021; de Gier et al. 2021; Richterman, Meyerowitz, and Cevik 2022; Lipsitch and Kahn 2021; Braeye et al. 2021).

[5]From the network theory perspective, prioritizing other high-exposure groups, such as K-12 or the

with the fewest non-elective interactions could more effectively reduce the likelihood of both contracting and spreading the virus, compared to public-facing essential workers, such as cashiers at a grocery or convenience stores (Milligan et al. 2021).[6] Therefore, I expect to see lower rates of contagion in states that prioritized grocery employees earlier in the vaccine eligibility queue.

I test this prediction using a matched sample of counties from two contiguous, Democratic-governed states—Oregon and California. Both states implemented similar policy responses to the Covid-19 pandemic in terms of school closures, stay-at-home orders, and mandatory mask mandates (Adeel et al. 2020). Even more importantly for this study, both California and Oregon prioritized grocery workers in Phase 1b, before the general public. The practical difference, however, is that, due to a confluence of idiosyncratic factors, Oregon lagged California in terms of the actual eligibility date for grocery employees by about a month. Consistent with the predictions of network theory, county-level statistical analysis shows that prioritizing grocery store employees led to a substantial reduction in new Covid-19 infections, and this effect grew stronger over time.

With the Covid-19 pandemic still underway, this research provides a theory- and data-informed cost–benefit analysis of giving higher priority to public-facing essential workers, such as grocery store employees. A key nuance is that, while carrying a disproportionately high potential for spreading the virus, grocery employees make up only a small fraction—less than 1 percent—of the population. To put this into perspective, even given the initial vaccine scarcity, vaccinating every single grocery employee would have delayed vaccine access for

incarcerated, should have a more limited effect on contagion among the general public. The reason is that these groups' interactions exhibit a clique-ish structure: individuals within groups come in frequent interaction with one another, but interact with few individuals outside of the group (Milligan et al. 2021). Should a single member of a clique get infected, the entire clique comes under high risk. Because cliques have limited interactions with non-clique members, however, infecting a clique only marginally increases the risk of infection for the general public.

[6] The pandemic, and the policy measures taken as a response (e.g. stay-at-home orders), only intensified two known patterns of social interactions: assortativity by age (most of daily interactions happen among individuals within the same age group) and a drastic decrease in the number of interactions with age (Brankston et al. 2021; Feehan and Mahmud 2021). As Brankston et al. (2021) and Feehan and Mahmud (2021) show, early in the pandemic, individuals of all ages reported very few non-household contacts; by September 2020, however, individuals aged 18 to 29 reported an increase in work- and school-related interactions. Just as prior to the pandemic, individuals aged 65 and older reported the highest level of social isolation.

other groups by less than a week—a negligible delay given the substantial effect on reducing case numbers shown here.[7]

By fleshing out the trade-offs of different priority sequences, this article opens an informed conversation about the benefits and costs of public health policies, as they relate to political trust and participation (Mattila 2020), inequality (Lynch 2020), long-term institutional development (Gingerich and Vogler 2021), and international cooperation (Norrlof 2020). Beyond vaccine distribution, this article also contributes to the study of the core political problem of the distribution of scarce resources more broadly. Remarkably, the analyses show, and explain, how the most politically-charged and controversial decision-making of the pandemic—vaccine prioritization—produced a seemingly apolitical outcome. As I demonstrate, vaccine priority lists did not clearly align with the usual political cleavages. Despite the high levels of political polarization throughout Trump's presidency and the pandemic, governors appeared to have prioritized the goal of effective policy response and demonstrating competency in a time of crisis, rather than distributing the scarce vaccine so as to buy off political supporters. With this example as a starting point, future research could explore the conditions that induce politicians to act on behalf of the entire electorate rather than cater to more narrow partisan interests.

This research also contributes to the general understanding of contagion and its pathways. Within studies of diffusion and network analysis, scholars have long applied models of disease contagion to study the spread of information (Lohmann 1994), censorship (King, Pan, and Roberts 2013), protests and repression (Siegel 2011; Van Belle 1996), social movements

[7] In December, 2020–January, 2021, Oregon was receiving about 50,000 vaccine doses per week (Botkin 2021) and California was receiving about 500,000 per week (CVAC Jan. 12, 2021, 6). There are 313,045 grocery employees in California and 37,491 in Oregon (US Department of Labor 2020). In comparison, other groups of essential employees prioritized by both states for early vaccine access, amounted to much larger numbers: medical employees—2.4 million in California and 0.4 million in Oregon, K-12 teachers and staff—1.3 million in California and 0.1 million in Oregon; food and agriculture—3.4 million in California and 0.2 million in Oregon. In relative terms, healthcare employees, K-12 teachers and staff, and agricultural workers account for 6, 3.6, and 8 percent of California's population, respectively, while grocery employees account for 0.8 percent. In Oregon, the comparable figures are 10 (health care), 2.5 (K-12), 4 (agriculture), and 0.9 percent (grocery). California numbers were obtained from CVAC meeting summaries of Dec. 9, 2020, (17), Dec. 16, 2020, (18) and Nov. 25 (15); Oregon numbers are from Botkin (2021), Oregon Health Authority (2022), and OHA (2020).

(Ayoub, Page, and Whitt 2021), and diffusion of policy innovation (Desmarais, Harden, and Boehmke 2015). While many studies emphasize the importance of central nodes for network diffusion processes, empirical tests of the posited causal effects are often impeded by the lack of data to approximate the counterfactual outcome (i.e., had the central nodes been removed from the network). For example, one cannot observe what a policy diffusion process across US states would look like in the absence of New York and California, or what the post-World War II international alliance network would look like without the United States. The variation in the Covid-19 vaccine distribution among US states, however, allows for a unique opportunity to empirically evaluate and isolate the causal effect of a handful of highly connected actors on the transmission rate within a network by varying the central actors' transmission ability between the treatment group (networks with the vaccinated central actors) and the control group (networks with the unvaccinated central actors), before and after the start of the treatment (vaccine eligibility for grocery employees), while holding all else constant (via matching). This design permits for a direct comparison between the observations in the treatment and control groups.

The article proceeds in the following way. After describing alternative vaccine prioritization plans, and the process that led to their formulation, I contextualize each within network theory. Next, I compare the effectiveness of vulnerability-based prioritization to an approach that targets public-facing essential workers, using a simulation experiment. I then introduce the data and research design, present and discuss the statistical analysis, and conclude.

## The Politics Behind Vaccine Allocation

As the FDA gave emergency approval to two Covid-19 vaccines in late November, 2020, numerous groups—from teachers to fast food employees, to morticians, to commercial pilots—made their bids for early vaccine priority. With the Trump administration delegating vaccine distribution to states, all eyes turned to the governors' offices.[8] The CDC (2021a) issued a set

[8]In the US, governors assumed the main decision-making power related to vaccine distribution (Adeel et al. 2020).

of broad recommendations: (1) "decrease death and serious disease as much as possible"; (2) "preserve functioning of society" and (3) "reduce the extra burden Covid-19 had on people already facing disparities." Given the high stakes and climbing death rates, these guidelines were interpreted as a justification for offering vaccine priority to the most at-risk individuals, such as medical workers and the elderly.

Once the vaccination campaign moved beyond these groups, however, the CDC guidelines as to further prioritization lists were less clear. Notably, in light of persistent vaccine shortages,[9] the first two goals were somewhat contradictory: decreasing deaths required continuing to prioritize vaccine access for the most vulnerable, whereas maintaining a functioning society necessitated inoculating individuals based on occupational risk of exposure. Without any additional clarifications from the CDC, states formulated vaccine priority lists using their best judgement.

One strategy was to continue prioritizing vaccine distribution based on vulnerability, using age, from oldest to youngest, as a proxy for mortality risk. Governor Holcomb, of Indiana, for instance, justified his state's strict adherence to vulnerability-based prioritization pointing to a strong correlation between age and hospitalization and death rates in his state (Salameh 2021). At the time, individuals aged 50 and older, while accounting for just over 35 percent of the Indiana's population, made up 80 percent of the Covid-19 hospitalizations and 98 percent of all Covid-19 deaths (Darling 2021).[10]

An alternative strategy was to also prioritize individuals with the highest risk of occupational exposure. In particular, this strategy raised priority for essential frontline workers[11]—individuals whose jobs were crucial to maintaining essential services and who, due to the nature of their work, could not maintain a safe distance from their co-workers or other individuals. Vaccinating people within these sectors ensured a continuation of essential

[9] In the US, vaccine supplies remained scarce until around May 1, 2020, when almost all states expanded eligibility to everyone 18 and older (American Journal of Managed Care 2021).

[10] These numbers were consistent with the national statistics (CDC 2020).

[11] The CDC defines frontline essential workers as distinct from essential healthcare workers. Specifically, frontline essential workers are "the subset of essential workers likely at highest risk for work-related exposure [...] because their work-related duties must be performed on-site and involve being in close proximity (<6 feet) to the public or to coworkers" (Dooling et al. 2021, 1657). Examples include grocery and manufacturing workers.

services while reducing the risk of infection for the individuals performing these services.[12] Some critiqued this prioritization plan on the grounds that, individuals in these occupational groups tend to skew younger and face lower overall health risks from contracting the virus.

Devising an effective, inclusive, and equitable vaccine prioritization plan became a test of a governor's competency, with the expectations rising as vaccine scarcity became more apparent. In these conditions, most governors created numerous vaccine task forces, including vaccine advisory committees that held regular public meetings, so as to enhance the transparency of decision-making. In contrast to earlier pandemic-related health policies, wrought with deep partisan divisions (Neelon et al. 2021; VanDusky-Allen and Shvetsova 2021), Covid-19 vaccine distribution plans exhibited a high degree of consensus. At least at the administrative level, both Democratic and Republican-led states agreed that the immediate goal was to distribute vaccines in a way that would minimize hospitalizations and deaths, with the broader goal of controlling the spread of the virus by vaccinating the largest number of people within the shortest possible time-frame.

Under these constraints, the outcome of the most scrutinized decision-making of the pandemic—which groups will receive priority in the vaccine line—turned out to look remarkably non-partisan, that is orthogonal to constituency preferences of decision-makers. For instance, Table 1 displays a mean comparison between the states that opened vaccine eligibility to grocery employees prior to March 1, 2021 (the date of eligibility in California) and those with later eligibility dates, on key demographic and other variables. The demographic variables here proxy possible political divides, such as urban/rural, education, ethnic/racial, economic, and age. Had vaccine priority lists been designed so as to deliver direct benefits (vaccines) to the most likely voters, one would be able to discern predictable systematic differences across these dimensions. The two groups, however, look very similar. An overall $\chi^2$ balance test fails to reach statistical significance (p-value=.2), which means that we cannot reject the null that there are no differences between the two groups.[13]

[12] Among different types of essential employees, public-facing employees, such as grocery store workers, carry a uniquely high risk of spreading the virus to the general public (Milligan et al. 2021).

[13] These results are replicated using survival analyses that treat time to eligibility for (a) grocery employees, and (b) individuals aged 65 and above as the dependent variables. These additional tests are available in

Table 1: A Comparison of States with Early/Late Vaccine Prioritization for Grocery Workers

| Variable | On/Before March 1 | After March 1 |
|---|---|---|
| Republican Governor | 0.31 | 0.61$^\dagger$ |
| State GDP/capita, logged | 4.13 | 3.97$^*$ |
| Median Age | 37.72 | 38.62 |
| State Population, logged | 15.32 | 15.11 |
| Median Income, thousands | 65.60 | 62.24 |
| Unemployment Rate | 0.35 | 0.36 |
| Percent BA Degree | 0.20 | 0.19 |
| Urbanization | 0.64 | 0.59 |
| Percent Black | 0.14 | 0.10 |
| Percent Latin | 0.16 | 0.11 |
| Biden's Margin | 0.06 | −0.03 |
| CumCovid/1000 (on 12-16-2020) | 12.20 | 11.86 |
| $\chi^2$ | 15.8 | |
| df | 12 | |
| $p$-value | 0.20 | |

Notes: $^*p < 0.05$, $^\dagger p < 0.1$.

The two groups differ on only two variables, neither of which is demographic: GDP/capita, which is a proxy for state capacity, and the party of the governor. The difference in the GDP/capita is controlled for in the statistical analysis; in the matched sample, counties are also matched on this variable. Had the difference between Republican- and Democratic-led states stemmed from a strategy to reward, or electorally target, constituents—otherwise, we would expect differences in terms of the demographic variables.[14] Moreover, the timing of

Appendix F.

[14]This difference is not well explained by an electoral impetus to prioritize the elderly, as the two groups are not significantly different in terms of median age. Moreover, in the 2020 Presidential election, Republican vote share advantage among individuals aged 65 and over was 4 percentage points (out of the two main parties vote)—the smallest of the four age groups, broken down by in Igielnik, Keeter, and Hartig (2021). Alternatively, this difference may have stemmed from a belief among Republican governors that prioritizing the based on age is more effective at minimizing deaths. Since prioritizing individuals over 64 is uncorrelated with the state demographics, in particular, median age, this type of potential selection into treatments is akin to an example, given by Imbens and Rubin (2015, 265), in which a doctor uses information on the amount of insurance coverage when deciding whether to prescribe their patient drug A and drug B. The treament is exogenous, as long as insurance was purchased prior to the diagnosis. In other words, unconfoundedness still holds, as long as the unobserved differences that resulted in unit assignment to the treatment/control conditions "are independent of the potential outcomes, conditional on observed covariates" (Imbens and Rubin 2015, 265).

vaccine access for grocery workers does not appear to result in large partisan benefits or costs: grocery employees are not a sizable voting bloc, are characterized by low levels of political participation, and are not organized/unionized in most states (US Department of Labor 2022).[15]

Qualitative analysis of vaccine advisory committee materials in Oregon and California, presented in Appendices D and E, further re-affirms this somewhat surprising result, as well as offers more insight as to the process that led to it. In particular, the case studies reveal a high degree of similarity in the two states' decision-making, a high degree of reliance of health authorities, and a general reluctance to deviate from the national guidelines.

Early in the process, for example, both states considered implementing a combination of an age-based and an exposure-based approach. In the end, the determining factor turned out to be the timing of a sudden change in the CDC guidelines with respect to the progress in each state's planning. With no advance notice to the states, on January 12, 2021, the CDC issued a revised guideline that the states prioritize vaccine based on age alone and expand eligibility to individuals aged 65 and above (CVAC Jan. 12, 2021, 3; Brown 2021b). Both states complied with this revised recommendation. At the time of the change, however, California happened to be slightly ahead of Oregon in its planning and progression through the vaccine priority list: in fact, California's Governor Newsom had already announced eligibility dates for several groups, including grocery employees, and several small counties had already been contacting these groups for a few days. As a result, while Oregon responded to the change in the CDC guidelines by simply moving to an age-based approach, California kept the already announced priority level for several exposure-based groups, though in practice, these groups were still pushed back in line behind the newly added age-based priority group. In other words, the choice of prioritization approach was not as set in stone as it may appear without the context. Had the change in the CDC guidelines not taken place, we may have well seen more states, including Oregon, give earlier priority to grocery employees.

In summary, the evidence suggests that vaccine distribution was less about divvying

[15] Since both California and Oregon are Democratic-governed and have similar proportions of grocery workers, this difference is irrelevant for the main analysis.

up resources among political supporters and more about demonstrating competence, or minimizing political fallout, in a situation with high political risk and uncertainty (Gasper and Reeves 2011; Quiroz Flores and Smith 2013; Ashworth, Bueno de Mesquita, and Friedenberg 2018).

## Network Theory and Vaccine Prioritization

From the perspective of network theory, the nature of contagion—its speed, reach, and main pathways of transmission—depends on the local structures within the network (Chyzh and Kaiser 2019). Rather than simply a function of network density, the rate of contagion depends on the presence of a few highly connected actors with cross-cutting connections to otherwise disconnected parts of the network (Granovetter 1973; Feld 1991; Padgett and Ansell 1993). What ultimately determines an actor's transmission potential is its level of connectedness or *centrality*.[16] It follows that, as long as there is some level of heterogeneity in actors' centrality (i.e., some actors have more direct or indirect connections than others), disabling the transmission potential of the network's most central actors is the fastest and most effective way to reduce or stop contagion.

By implication, individuals who are the most likely to limit their social interactions as to protect themselves against the virus (e.g., due to a pre-existing condition), effectively self-select themselves into less central network positions. Prior to widespread vaccine availability, most of the general population dramatically reduced their social interactions, with the highest level of social isolation reported by individuals aged 65 and older (Brankston et al. 2021; Feehan and Mahmud 2021). Since essential-service providers are the toughest social links to eliminate, giving vaccine priority to essential frontline workers is also an effective way to reduce the risk of infection for the most vulnerable individuals.[17] Conversely, age-based

[16]Measures of centrality include *degree*, *eigenvector*, *closeness*, and *betweenness centrality* (Bonacich 1972; Patty and Penn 2017). See Appendix A for formal definitions.

[17]This logic also applies to reducing contagion for the individuals with the highest vulnerability due to living arrangements, such as nursing homes. From a network perspective, individuals who work on live in close proximity to others are a clique—a network component in which every individual comes in contact with every other individual. The property of a clique—and a partial reason of the high pandemic death rates in nursing homes—is that infection of a single member poses a high risk of infection of the entire clique.

vaccine prioritization is less likely to reduce or stop the spread of the virus, as the key transmitters, individuals in entry-level positions, such as front-facing grocery employees, tend to fall within a younger age range.

To explore how these well-known theoretical insights work within this specific application, I compare the effects of vaccine prioritization plans (centrality- vs. vulnerability-based) using a simulation experiment based on a real-world human interaction network. I start by defining the nodes in a network as a set of $n$ actors $i \in \{1, 2, \ldots, n\}$, and one or more interactions between each pair of nodes $i$ and $j$ as a link, $l_{ij} = 1$. To assess a node's transmission potential within a network, I use *degree centrality*, which is defined as the total number of its direct links, or $\sum_{j:j \neq i} l_{ij}$ (Bonacich 1972; Patty and Penn 2017).[18]

I begin with Coleman's (1964) widely-used dataset on a high school friendship network.[19] In this network, two individuals are connected by a link if at least one of them named the other as someone with whom they frequently interacted.[20] Figure 1 shows the distribution of individuals' degree centralities in these data.

Figure 2 shows the node with the highest value on degree centrality in dark red. Without loss of generality, assume that a virus spreads on contact with certainty. If the dark red node is the initial carrier (Patient 0), then its direct neighbors (shown in red) are the next to contract the virus, after which the virus spreads to the nodes that are reachable through a shortest path of length 2 (shown in orange) as a part of the second round.[21] The figure

Assuming that there is not enough vaccine to inoculate every member of the clique, the highest risk to the clique comes from its members' contacts that are external to the clique. As long as the vaccine is too scarce to inoculate every member of a clique, the best protection is to protect those who are indispensable for the cliques' functioning—medical workers and public-facing essential workers. This implication is even stronger given that, as we now know, the Covid-19 vaccines' effectiveness declines with individuals vulnerability (Andrews et al. 2021; Nunes et al. 2021; Salmeron Rios et al. 2022).

[18] Degree centrality is the most common network metric for modeling a node's transmission potential. In Appendix B, I replicate the experiment using other common centrality metrics, such as eigenvector, closeness, and betweenness centrality. The choice of centrality measure does not substantively affect the results, as in social interaction networks, actors that rank high on one centrality measure tend to also rank high on other centrality measures.

[19] The dataset consists of a friendship network among 73 boys in a small high school in Illinois in Spring 1958 (Coleman 1964).

[20] I transform the original directed network data into a non-directed symmetric network.

[21] For each pair of nodes, the shortest path, $d_{ij}$ between $i$ and each other node $j$ in the network is the total number of links on the path between them. For example, the shortest path between two nodes that are connected by a link is of length 1. If $i$ and $j$ do not share a direct link, but $i$ is connected to $l$, and $l$ is

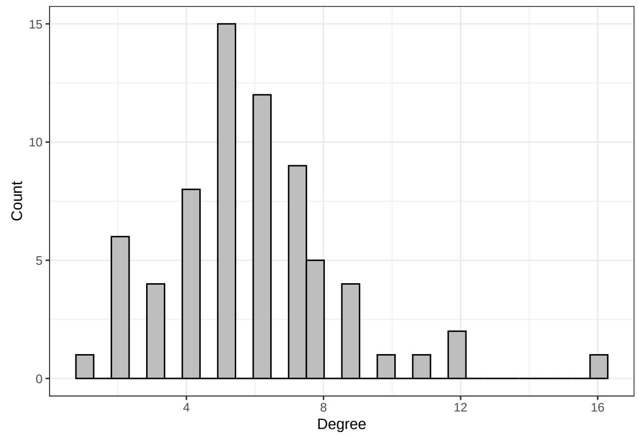


Figure 1: Centrality in the Interaction Network

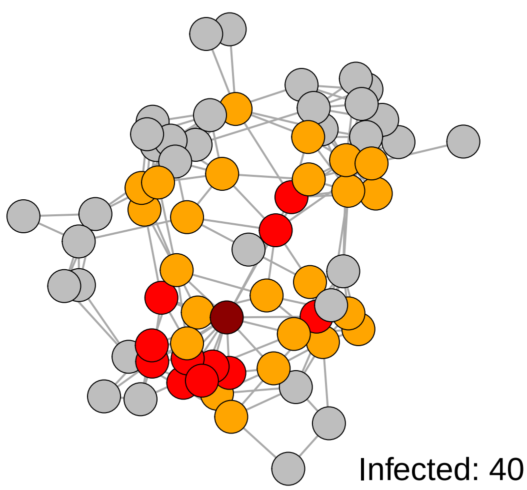


Figure 2: Contagion in the Interaction Network

shows that, for this network, choosing the node with the highest degree centrality as Patient 0 results in 40 infected individuals at the end of two rounds of contagion.

Now suppose there are 10 available vaccines. Without loss of generality, assume getting a vaccine makes an individual both immune to the virus and unable to transmit it. Figure 3 shows the spread of the virus under both the age- and exposure-based prioritization scenarios. Groups receiving priority based on age are less likely to be a part of the workforce, and, hence, have the greatest flexibility to limit their risk of exposure by reducing their number

connected to $j$, then the shortest path between $i$ and $j$ is of length 2.

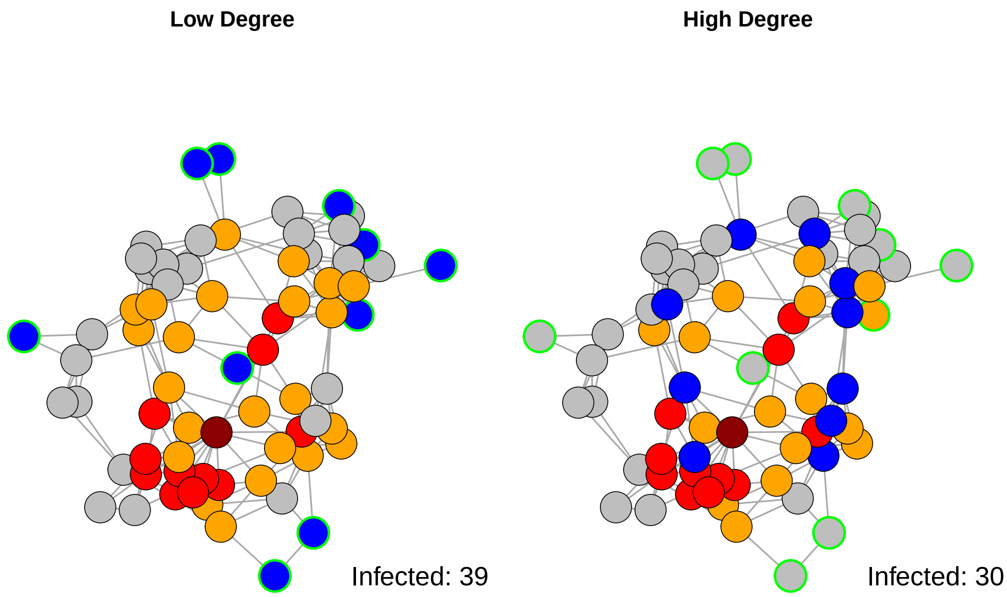


Figure 3: Vaccination Scenarios

of social interactions (i.e., they are willing and able to do so).[22] Therefore, to reflect this prioritization strategy within the simulation experiment, I define *vulnerable individuals* as those with the lowest degree centrality. Age-based prioritization, by implication, consists of allocating the 10 available vaccines based on degree centrality, from lowest to highest. I refer to this part of the simulation as the *Low Degree* scenario.

To reflect the exposure-based prioritization strategy, I define the individuals with the greatest risk of exposure as those with the highest degree centrality. Occupational risk vaccine prioritization, therefore, consists of allocating the 10 vaccines to the most central nodes in the network (other than Patient 0). This is the *High Degree* scenario.

The demonstration shows that the second vaccine prioritization strategy leads to a drastic reduction of contagion in the network: it results in 9 fewer cases of contracting the virus (a 30 percent reduction). For a network of 69 individuals (after removing isolates), this is a difference between infecting 57 vs. 43 percent of the nodes in the network. If we think of the nodes with the lowest degree centrality (marked with green border color in 3) as

[22]The network science focus limits our insights to groups of individuals that are identifiable as a function of their network connections. Making separate inferences for vulnerable individuals that are either unable or unwilling to self-isolate by reducing their number of direct contacts are treated is beyond the scope of this article.

Table 2: Round 2 Summary for 10,000 Simulations of the Interaction Network among 73 Individuals

| | Vaccinated | Infected | Not Infected | Vulnerable Infected |
|---|---|---|---|---|
| No Vaccine | 0 | 39.35 (5.40) | 28.65 (5.40) | 3.24 (1.51) |
| Low Degree | 10 | 36.04 (5.07) | 21.96 (5.07) | 0 |
| High Degree | 10 | 24.13 (4.74) | 33.87 (4.74) | 2.38 (1.38) |

*Note:*
Cell values are means over 10,000 simulations. Numbers in parentheses are standard deviations. *Not Infected* does not include *Vaccinated*.

vulnerable individuals, this demonstration also shows that the second vaccine prioritization scenario fares well at protecting these individuals: only one such node contracted the virus under the second scenario.

To generalize from this example, I perform the following Monte Carlo experiment. I start by estimating an exponential random graph model (ERGM) (Wasserman and Faust 1994), in which the interaction network is the dependent variable, and the network parameters of interest are the baseline link probability (*edges*), the tendency towards open triangles (*2-stars*), and closed triangles (*gwesp*)—the most common ERGM specification that models the basic features of a human interaction network.[23] The estimates of this model are shown in Appendix B. I then use the estimates from this model to simulate the interaction network 10,000 times, and repeat the analysis done on the original interactions network, on these simulated networks.[24]

Table 2 shows the mean (standard deviation) of the number of individuals infected/not infected at the end of the second round of contagion (individuals connected to patient 0 directly or via one intermediary) in 10,000 simulations of the interaction network. Just as before, I denote the 10 individuals with the lowest number of direct (lowest degree centrality) connections as "vulnerable" individuals. These are the individuals vaccinated in the *Low Degree* scenario. The last column of Table 2 shows the mean (standard deviation) of the

[23]ERGMs are an estimation approach for modeling the probability of observing a network with a given set of endogenous statistics, such as the total number of edges, open or closed triangles, or other network features (Hunter et al. 2008; Robins et al. 2007).

[24]For a similar simulation approach, see Boehmke et al. (2017).

number of vulnerable individuals that are infected under each of the vaccination scenarios. I also perform a simulation for a *No Vaccine* scenario for comparison.

Under the *Low Degree* scenario of giving vaccine priority to the vulnerable individuals, the number of individuals infected at the end of the second round is only slightly lower than that under the *No Vaccine* scenario (roughly 37 vs. 40). Under the *High Degree* scenario, the number of the infected is substantially lower: 12 fewer than under the *Low Degree* scenario, or a 32 percent decrease.

These results, of course, are based on the simplifying assumption that vaccine is 100 percent effective at both preventing virus contraction and transmission, and that the effectiveness does not change with vulnerability. Given that, in actuality, vaccine effectiveness decreases with vulnerability (Andrews et al. 2021; Nunes et al. 2021; Salmeron Rios et al. 2022), the results error on the conservative side, downplaying the difference in effectiveness between the two vaccine priority plans. If we relaxed this assumption and allowed the probability of virus transmission to increase with vulnerability, even for the vaccinated, the difference between the numbers of individuals infected under each vaccine priority plan would be even larger (i.e., among the vaccinated, vulnerable individuals would contract the virus at a higher rate than the more central nodes).

In summary, the results of the simulation experiment confirm that, in terms of reducing contagion, a centrality-based (i.e., exposure-based) vaccine prioritization plan substantially outperforms that of allocating vaccines based solely on vulnerability. The simulation highlights the effectiveness of vaccinating essential frontline workers for reducing the spread of Covid-19, compared to other vaccine prioritization strategies, under the conditions of vaccine scarcity or distributional constraints. States that prioritized vaccine access for essential frontline workers were able to reduce transmission by eliminating a key source of contagion—inoculating the individuals that came into contact with both the greatest number of people and societal groups. This leads to the following hypothesis:

*Research Hypothesis: Administrative units that prioritize individuals with higher centrality will experience fewer infection cases.*

## Research Design

To test the research hypothesis, I leverage variation in vaccine priority lists between California and Oregon, two neighboring Democratic-governed states that were similar in their pre-vaccine Covid-19 policies (Adeel et al. 2020). While early on, the two states followed a similar vaccine distribution strategy as the rest of the US (i.e., prioritizing the elderly and the medical workers), California was among the first states to extend vaccine eligibility to grocery store employees (on March 1), whereas in Oregon, grocery store employees did not become eligible for vaccination until almost a month later (on March 29). The unit of analysis is the county-day. The dependent variable is a logged 7-day rolling average of the number of new Covid-19 cases, obtained from the John Hopkins University Center for Systems Science and Engineering (Gassen 2021).[25]

The independent variable is an interaction between *California* and *Day of Treatment*, in which *California* is a binary variable that equals 1 for California and 0 for Oregon, and *Day of Treatment* is a count variable; the count starts at 1 on March 14, 2 weeks since grocery employees became eligible for vaccination in California—the date when those who had received the first dose would have achieved partial immunity (between 50–80%) (Polack et al. 2020; Bernal et al. 2021). The estimation equation is:

$$\begin{aligned} log(New\ Cases) = \beta_0 + \delta_0 Day\ of\ Treatment + \beta_1 California \\ + \delta_1 California \times Day\ of\ Treatment + other\ factors. \end{aligned}$$

This, of course, is a textbook example of the difference-in-difference design (Wooldridge 2015, 407–12). The *treatment* here is measured as the day since the first grocery workers had developed partial immunity in California (*Day of Treatment*). The estimation parameter $\delta_0$ is the average difference between the periods *before* and *after* the start of the treatment for the control group; $\beta_1$ is the average difference between the two groups *prior* to the treatment;

[25]The John Hopkins data contain cumulative data by day and US county. I calculated daily cases by first-differencing cumulative cases. In a small number of cases, first differencing resulted in negative numbers of cases, due to data corrections. Any such negative values were recoded to 0.

$\beta_1 + \delta_1$ is the average difference between the two groups *after* the start of the treatment, and $\delta_1$ is the difference-in-difference coefficient that gives the average difference attributable to the treatment (i.e., the average effect of expanding vaccine eligibility to grocery employees in California).

I control for a number of pre-treatment county-level demographic variables that may influence Covid-19 contagion, including the logged cumulative number of reported Covid-19 cases per 1000 residents (as recorded on December 16, 2020—the day prior to the first vaccines were administered in the two states), logged GDP (2019 USD), logged population, unemployment rate, percent of population that hold at least a Bachelor's degree, urbanization, percentage of black and other racial minorities, percentage of Hispanic/Latino population, percentage of foreign population, Biden's percentage margin in the two-party vote in the 2020 election, county-level proportion of residents of age 65 and above, and an indicator variable of whether a county was under a ban on indoor dining, bars, gyms, hair salons and related services prior to the start of the vaccine roll out.[26] Data on county-level economic outcomes were obtained from the Bureau of Economic Analysis, and the demographic variables from the most recent US Census American Community Survey (2015–19 averages). Unemployment data are 2019 numbers obtained from the most recently available decennial census. To address temporal autocorrelation in the data, I include a lagged value of new Covid-19 cases per 1000 residents, logged.[27]

To tighten the causal claims, I also implement a matched-sample design.[28] I matched

[26]Prior to the beginning of the vaccination campaign, the two states did not differ on other major Covid-19 prevention policy measures in a meaningful way (Adeel et al. 2020). Both states, for example, were under mask mandates (Hubbard 2022). Both states' primary, secondary, and tertiary educational establishments shifted to virtual instruction at the start of the pandemic in the spring of 2020 and stayed online until the end of the Fall 2020 semester (Mays 2021; Brown 2021a) and did not resume hybrid or in-person instruction until March, 2021 (Brown 2021a; Mays 2021).

[27]Diagnostics support using a three-period lag of the logged 7-day average in cases.

[28]A key benefit of matching is that, when applied to pre-treatment outcome levels, it ensures both balance between the treatment and control groups, as well as parallel trends in the pre-treatment period (Lindner and McConnell 2019, 129–30). When used in combination with a difference-in-difference design, however, a poorly specified matching model may introduce bias (Lindner and McConnell 2019). If the observable variables used in the matching model do not account for a significant portion of the variation in the outcome, then what one may interpret as the treatment effect may be in fact due to the unobserved and unmodeled confounders. Model fit statistics, such as the large adjusted coefficient of determination, indicate that this is not a concern in this application. Despite this, I follow best practices by reporting both adjusted (matched sample) and

Table 3: Matched Counties

| Oregon (11) | California (12) |
|---|---|
| Wheeler | Sierra |
| Wallowa | Mariposa |
| Union | Modoc |
| Linn, Klamath | Calaveras |
| Deschutes, Jackson, Polk, Yamhill | El Dorado, Lake, Nevada, Siskiyou |
| Marion | Placer, San Luis Obispo |
| Multnomah | Santa Barbara, Sonoma |

California counties (treatment group) with those in Oregon (control group) on all pre-treatment variables (other than *California* and its interaction with *Treatment Day*) using coarsened exact matching (CEM) (Iacus, King, and Porro 2012).[29] CEM consists of identifying exact matches (observations with the same values on all covariates) after coarsening (dichotomizing or multichotomizing variables into discrete categories) any continuous and ordinal variables. Per Iacus, King, and Porro (2012), I selected the number of cutpoints to multichotomize the variables using the empirical knowledge of the data, whenever possible. To maximize sample size, I allowed for multiple matches for each observation.

Table 3 displays the list of matched counties: 12 counties from California and 11 from Oregon. The matched sample includes a balance of coastal and inland counties. While it excludes several outlier-counties based on population size (e.g., Los Angeles county in California), it includes a mix of counties of various levels of population size and urbanization.

To assess the balance in the matched sample, Table 4 displays the standardized mean differences for each covariate, along with the corresponding $p$-values. California and Oregon counties in the matched sample are not statistically significantly different on any of the matching variables; the overall $\chi^2$ is also not statistically significant.

I estimate the model, on both full and matched samples, using OLS regression. The full sample consists of daily observations for all counties (58 in California, 36 in Oregon) between December 17, 2020 (the first day of vaccine administration in both states) and April 11, 2021

unadjusted (full sample) results (Lindner and McConnell 2019).

[29]The matching strategy accounts for vaccine availability by matching on county population—a key criterion used for vaccine allocation.

Table 4: Balance Between Oregon and California in the Matched Sample

| Variable | Std. Difference | $p$-value |
|---|---|---|
| County GDP, logged | $-0.13$ | 0.74 |
| County Population, logged | $-0.03$ | 0.94 |
| Unemployment Rate | $-0.48$ | 0.24 |
| Percent BA Degree | $-0.02$ | 0.97 |
| Urbanization | 0.15 | 0.71 |
| Percent Black | $-0.24$ | 0.55 |
| Percent Latino | $-0.67$ | 0.10 |
| Percent Other Race | $-0.51$ | 0.21 |
| Percent Foreign | $-0.53$ | 0.20 |
| Biden's Margin | $-0.34$ | 0.41 |
| Prop. Aged 65+ | $-0.49$ | 0.23 |
| Indoor Dining Ban | 0.04 | .93 |
| Cum. Covid, logged | $-0.11$ | 0.78 |
| $\chi^2$ | 15.7 | |
| df | 13 | |
| $p$-value | 0.26 | |

(two weeks after Oregon authorized giving vaccines to food processing employees, including grocery employees) for a total of 10904 non-missing observations, while the matched sample consists of 2668 observations.

## Results

Table 5 shows the results of the statistical analysis for the full sample (Model 1) and the matched sample (Model 2). Since the dependent variable, *New Covid-19 Cases* is measured on a logged scale, the model coefficients are interpretable as percent changes (Wooldridge 2015). Thus, the coefficient of 0.23 on *California* is statistically significant at $\alpha = .05$ (two-tailed test) and indicates that, *prior* to opening up Covid-19 vaccination to grocery store employees, the state of California has had, on average, about 23 (0.23*100) percent more new daily Covid-19 cases than the state of Oregon in the full sample. In the matched sample, however, this effect is no longer statistically significant at $\alpha = .05$ (two-tailed test).

The coefficient of $-0.009$ ($-0.011$ in the matched sample) on the *Day of Treatment* gives the average difference in new Covid-19 cases in Oregon counties before and after California

Table 5: The Effect of Vaccine Eligibility to Grocery Employees on New Daily Covid-19 Cases (logged)

| | Full Sample | Matched Sample |
|---|---|---|
| Day of Treatment | $-0.009^{***}$(0.001) | $-0.011^{***}$(0.002) |
| California | $0.229^{***}$(0.021) | $-0.036$ (0.043) |
| California∗Day of Treatment | $-0.039^{***}$(0.002) | $-0.030^{***}$(0.003) |
| Cumulative Cases, logged | $-0.117^{***}$(0.022) | $-0.295^{**}$ (0.098) |
| County GDP, logged | $0.350^{***}$(0.023) | $-0.571^{***}$(0.095) |
| County Population, logged | $0.376^{***}$(0.022) | $1.150^{***}$(0.120) |
| Unemployment Rate | $-0.018^{***}$(0.002) | $-0.045^{***}$(0.013) |
| Percent BA Degree | $0.021^{***}$(0.003) | $0.052^{***}$(0.006) |
| Urbanization | $0.008^{***}$(0.001) | $0.011^{***}$(0.001) |
| Percent Black | $0.044^{***}$(0.004) | $0.213^{***}$(0.043) |
| Percent Latino | $0.030^{***}$(0.001) | $0.066^{***}$(0.007) |
| Percent Other Race | $0.026^{***}$(0.001) | $0.024^{***}$(0.006) |
| Percent Foreign | $-0.045^{***}$(0.002) | $-0.059^{***}$(0.014) |
| Biden's Margin | $-0.010^{***}$(0.001) | $-0.010^{***}$(0.002) |
| Prop. Aged 65+ | $3.716^{***}$(0.266) | $12.078^{***}$(1.874) |
| Indoor Dining Ban | $0.084^{**}$ (0.026) | $-0.814^{***}$(0.142) |
| New Cases/1000 res., 3-day lag | $0.213^{***}$(0.004) | $0.132^{***}$(0.007) |
| Constant | $-7.185^{***}$(0.177) | $-3.403^{***}$(0.585) |
| Num.Obs. | 10904 | 2668 |
| $R^2$ Adj. | 0.89 | 0.87 |

$^{***}p < .0.05$ (two-tailed), $^{*}p < 0.1$ (two-tailed).

opened up vaccination to grocery employees. This coefficient is statistically significant, indicating that Oregon experienced about 1 percent decrease, on average, in new daily Covid-19 cases in the period since March 14, 2021 compared to the period between December 17, 2020 and March 14, 2021.

The coefficient of -0.04 (-0.03 in the matched sample) on the interaction term is the difference-in-difference coefficient. It indicates a 4 percent decrease (3 percent in the matched sample) in new Covid-19 cases in California (compared to Oregon), since California opened vaccine eligibility to grocery employees. This coefficient, of course, gives us only the average daily effect, as *Day of Treatment* is measured on an integer scale.[30] The marginal effect of *California* by *Day of Treatment*, is shown in Figure 4. As one can see, the effect of vaccinating

[30] Results are robust to coding *Day of Treatment* on a nominal scale or including polynomials. Diagnostics favor the model presented in Table 5.

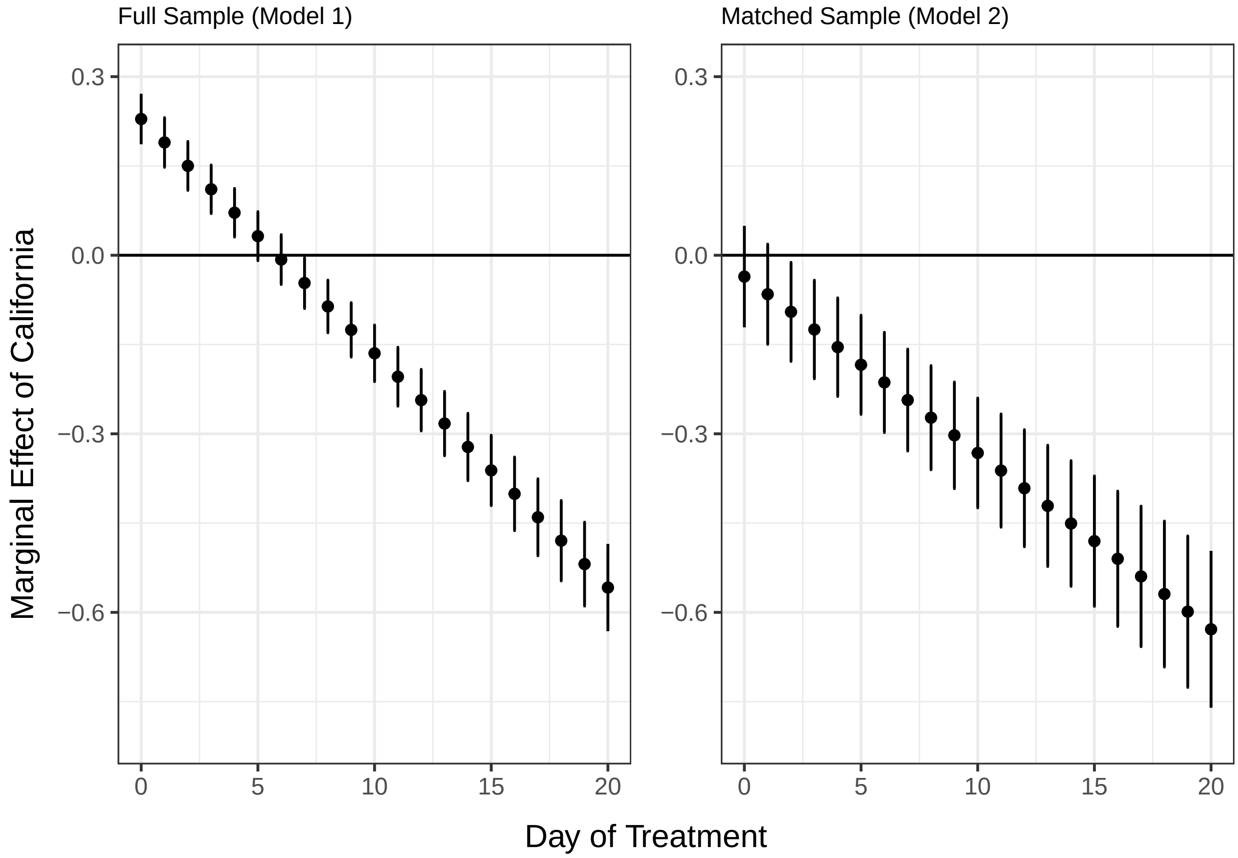


Figure 4: Marginal Effect of Vaccine Eligibility to Grocery Workers. Error bars represent 95% CIs.

grocery employees results in about 43 percent decrease in cases $((\exp(-.56) - 1) \times 100\%)$ (about 46 percent in the matched sample) 20 days after the start of the treatment period. These results provide strong support for the research hypothesis. Similar results also hold for the outcomes of Covid-19-related hospitalizations and deaths.[31]

**Validating Model Assumption**

Interpreting the model's estimates in causal terms rests on several assumptions, such as the Stable Unit Treatment Value Assumption (SUTVA), cross-sectional and temporal treatment exogeneity, and parallel trends. In this section, I discuss the validity of each assumption in the context of the current application.

**SUTVA.** The first assumption, the Stable Unit Treatment Value Assumption (SUTVA),

[31] These additional results are presented in Appendix F.

which requires that treatment assignments for other units do not affect the outcome for unit $i$, and that each treatment defines a unique outcome for each county (Imbens and Rubin 2015, 33). The first part of SUTVA—that participants cannot interfere with the assigned treatments—is met as long as Oregon grocery workers cannot travel to California to receive the vaccine ahead of their turn. Though technically possible (California did not require proof of residency for vaccine appointments), any such instances would be costly: an employee would have to get informed on how to register for an appointment in a difference state, take time off work and travel, in many cases, a significant distance. Hence, any such violations would be rare. Were this type of interference pervasive, this would induce downward bias in the estimate of the average treatment effect, i.e. make it more difficult to detect a difference between the treatment and the control group.

A secondary part of SUTVA is that each unit in the treatment group receives the same "dose" of the treatment. This assumption would be violated, for example, if counties varied in terms of vaccine take-up among grocery employees. I account for this and other possible unobserved differences among observations by including control variables, and in the matched sample, by matching on the observable sources of variation. A weaker variant of the "equal dose" assumption is that the unobservable differences that may induce the variation in the treatment dose are correlated with the observable control variables included in the model (Imbens and Rubin 2015, 9–13; Stuart 2010, 3).

**Treatment Exogeneity.** The second assumption is unconfoundedness or treatment exogeneity. Exogeneity implies that the treatment and control groups are equal, on average, on all observed and unobserved variables that may affect the outcome variable, with the exception of the treatment and confounders for which the researcher controls (Sekhon and Titiunik 2012, 36; Imbens and Rubin 2015). While in randomized controlled experiments, this assumption is a function of random assignment of research participants to the treatment and control group by the researcher, natural experiments lack a comparable iron-clad validity guarantee. In quasi-experimental design, the validity of the exogeneity assumption hinges on whether the researcher can provide a compelling justification.

I justify this assumption using three alternative and self-reinforcing strategies: with statistical evidence; via the research design, which includes matching on observables (Imbens and Rubin 2015); and analytically, by using evidence from case studies of California and Oregon's decision-making (Dunning 2008). The statistical evidence consists of the analysis of the national determinants of vaccine prioritization, discussed earlier, and placebo tests, presented later in this section.

In addition to implementing a matched design, the research design also helps alleviate unit self-selection concerns by de-coupling the treatment assignment (at the state level) from the unit of observation (counties). No general one-size-fits-all prioritization plan, even the one tailored to the demographics of the state, would apply equally well at the county level, especially in states as diverse as Oregon and California. Oregon's Multnomah county, which includes Portland, has very different demographics than any of the counties east of the Cascades. Self-selection at the state level, in other words, would not translate into self-selection at the county level, as long as the demographics of individual counties do not precisely match those of the entire state.[32]

For space consideration, the full analytical justification in presented in Appendix D. In brief, the novelty of the virus, and the lack of information regarding its spread, effectively set up a natural experiment of policy-making under conditions of incomplete information. Earlier in the pandemic, these conditions resulted, for example, in many states implementing controversial and, in retrospect, unnecessary measures of closing down beaches and national parks.[33] Likewise, most state-level decisions related to vaccine prioritization were also made under conditions of very limited information, as the first vaccines were given emergency approval before various aspects of their effects were fully evaluated. In particular, early distribution plans were made in the absence of reliable information on whether vaccines reduced transmission of the virus, prevented disease, or merely ameliorated the symptoms; a sufficient body of evidence showing that vaccines were effective at reducing transmission did

[32]Individual counties had very limited discretion over vaccine prioritization, mainly with the aim of avoiding wasting doses (CVAC Jan 12, 2021, 12).

[33]These policies were shown to be unnecessary, once the evidence emerged that the virus transmission is significantly reduced in non-confined spaces.

not become available until mid-March 2021, long after the prioritization plans were finalized (Christie, Mbaeyi, and Walensky 2021; CDC 2021b).[34] A systematic correlation between the treatment assignment and the outcome requires expertise—a reasonable expectation of which treatment would work best for each unit. In the absence of such expertise, however, the assignment mechanism is not that different from tossing a coin or rolling a die. In other words, an uninformed decision-maker approximates a randomization mechanism.

Further evidence that the governor offices did not act on a set agenda comes from both states' strict adherence to the national guidelines, and willingness to quickly modify previously formulated plans in response to sudden changes in national guidelines, such as the unexpected January 12 revision to the previous recommendation of prioritizing based on both age and exposure. In response to that change, both states shifted to the now recommended age-based prioritization plan, with the exception of groups whose eligibility had already been announced, such as Oregon's K-12 employees and California's grocery employees.

**Temporal Treatment Exogeneity.** Related to unconfoundedness is the assumtion that the treatment does not influence the pretreatment population, that is, that opening vaccine eligibility to grocery workers does not affect Covid-19 cases in the preceding time-period (Lechner 2011). An example of this would be California grocery workers taking extra precautions to avoid contracting Covid-19, for example, by wearing masks, in anticipation of getting the vaccine. They might have reasoned, for example, that it is worthwhile to incur some additional inconveniences for several weeks, so as to avoid contracting the virus right before getting the vaccine. Had this been systematically the case, we would observe evidence of the treatment effect prior to the start of the treatment. The placebo tests, discussed below, show no evidence of such an effect.

**Parallel trends assumption** Finally, the model relies on the parallel trends assumption.

[34] Though there was a working hypothesis among medical researchers that vaccinations may reduce transmission—owing to fewer of the more contagious symptomatic cases and reduced viral loads among vaccinated individuals (Mallapaty 2021; Levine-Tiefenbrun et al. 2021)—there was little direct evidence in late 2020, when prioritization distribution plans were being drafted. Moreover, there was no consensus opinion within the medical community: some researchers offered a countering view, arguing that vaccinated individuals could still carry and spread the virus, even if they themselves were largely protected (e.g., Bleier, Ramanathan, and Lane 2021). Even as evidence changed, most states stuck by their pre-determined prioritization plans.

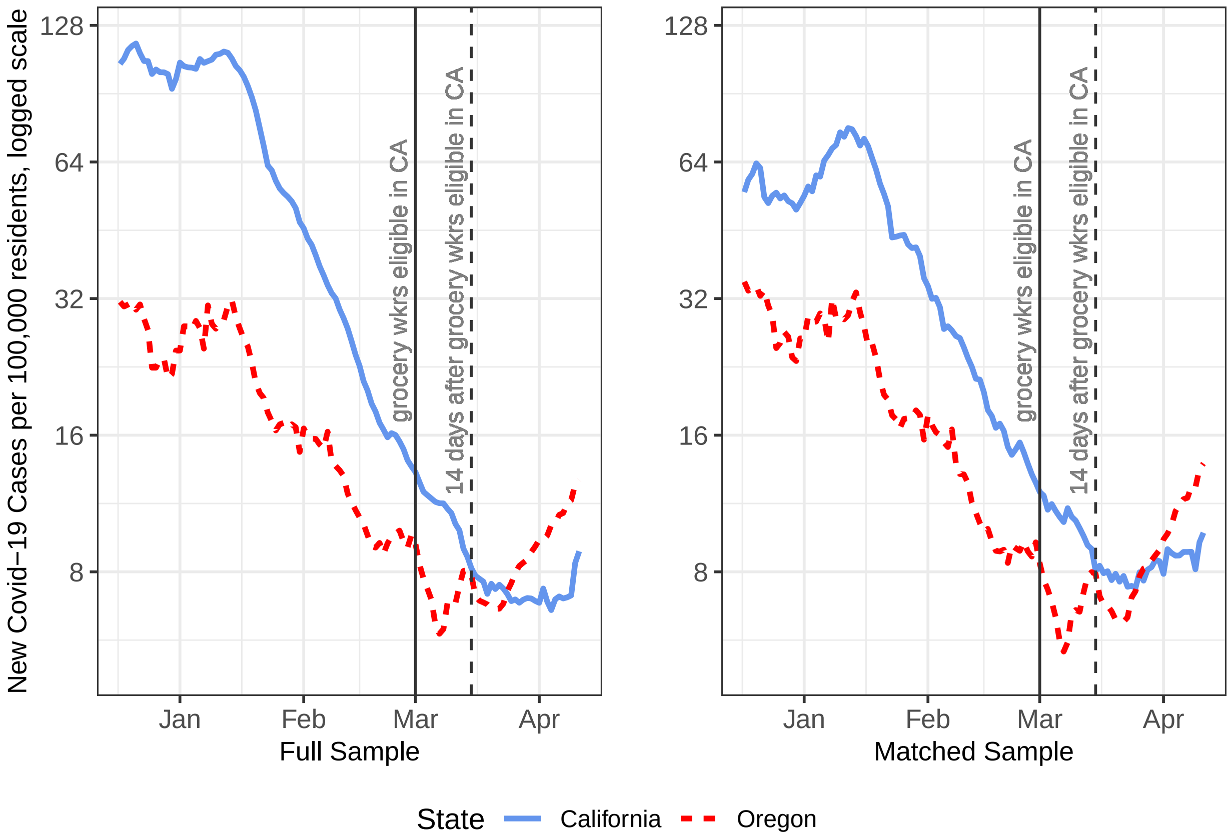


Figure 5: Temporal Trends (State Averages) in Covid-19 Cases, December, 2020–April, 2021.

This assumption requires that, after controlling for observable confounders, changes in expected non-treatment outcomes between the time periods before and after the treatment are mean independent of the treatment assignment (Lechner 2011). If this assumption holds, then difference-in-difference estimation recovers unbiased estimates of the average treatment effect for the treated.

Figure 5 shows the temporal trends in the raw data (on the left) and in the matched sample (on the right). Both subfigures show that the daily number of new Covid-19 cases followed a similar trend in the two states between the start of vaccinations in December 2020 and the middle of March, 2021: both experience a brief period of increasing cases between early to mid-January, 2021, followed by a consistent decline up until early March. In the matched sample, the aggregate difference in new Covid-19 cases between the two states was about 460 daily new cases on December 17, 2020. This difference narrows to about 222 new cases by February 15, 2021, and further to about 86 by March 1, and to 12 cases by the start

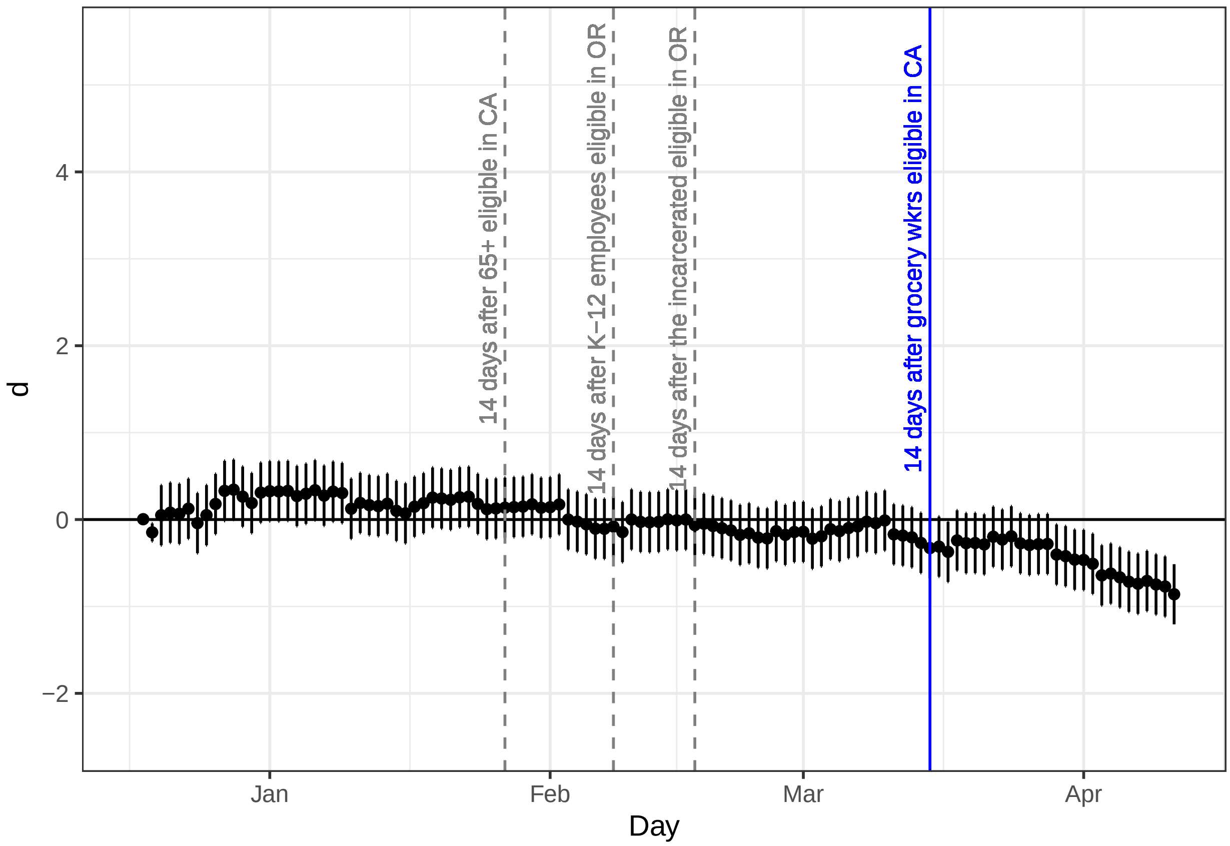


Figure 6: Daily changes in the Difference Between California and Oregon, $\delta_{1t}$, Matched Sample. Error bars represent 90% CIs.

of the treatment on March 15.

In the treatment period, as California expanded vaccine eligibility to grocery store employees on March 1, 2021, whereas Oregon did not, the two trends diverge. The point of divergence falls somewhere between March 1 and March 15—the latter date is when the grocery employees who had been vaccinated on March 1 would have achieved between 50–80% immunity. After this time, the trend of new Covid-19 cases in California continues to decline, whereas Oregon starts observing an increase. At this point Oregon surpasses California in the aggregate cases in the matched sample, its lead reaching about 69 daily new cases by April 11, 2021 (2 weeks after Oregon also opened vaccine eligibility to grocery workers).

While the pre-treatment trends look similar, especially between mid-January and mid-March, whether they are indeed parallel is ultimately a subjective judgement. Though one cannot directly test the null hypothesis that the slopes of the two trends are the same, it is possible to test whether the difference between the slopes is statistically different from zero. To do this, I estimated the following model:

$$\begin{aligned} log(New\ Cases) = \beta_0 + \sum_{t=1}^{T-1} \delta_{0t} Day_t + \beta_1 California \\ + \sum_{t=1}^{T-1} \delta_{1t} Day_t \times California + other\ factors, \end{aligned}$$

where $Day_t$ is a set of $T-1$ indicator variables for each day $t \in \{1, 2, \ldots, T-1\}$ included in the sample, $\delta_{0t}$ is a set of daily intercepts, and the coefficients $\delta_{1t}$ on the interactions between *California* and each of the daily dummies are estimates of the daily changes in the difference between California and Oregon in the sample.

Figure 6 displays the coefficients, $\delta_{1t}$, on the interaction terms for each day. The daily changes are not statistically different from zero for most of the pre-treatment period. The pre-treatment mean is 0.09; it drops to -0.13 shortly after California expands vaccine eligibility to grocery workers, and further to -0.45 in the treatment period. I interpret this as (indirect) support for the parallel trends assumption. As additional support for the research hypothesis, the coefficients become statistically significant for the majority of the post-treatment period, and the trend line is increasing in magnitude. In summary, the above placebo tests show no discernible pre-treatment trends in the matched sample.

One may also define the dates that correspond to other differences between the two states' vaccine priority lists as pseudo-treaments. Since the timing of grocery employee eligibility was the only theoretically relevant difference, we expect that these pseudo-interventions have no effect on the number of Covid-19 cases. Other than food and agriculture (which included grocery employees), the two states differed on the sequence and timing of several other groups, most prominently, teachers, and the incarcerated.[35] California also had a less expansive definition for Phase 1a, which put it 12 days ahead of Oregon in opening Phase 1b.[36] Taking

[35] Oregon opened vaccine eligibility for teachers on January 25, 2021, and to the incarcerated on February 3, 2021. In California, in contrast, teachers were not eligible until March 1 and the incarcerated until March 15.

[36] While California's definition of health workers was limited to any personnel with direct interaction with patients, Oregon had no such qualifications and also included any non-medical personnel of healthcare facilities, such as cleaners and food servers (OVAC, Jan. 14, 2021). In addition to healthcare workers, both states' Phase 1a included residents of long-term care facilities (CVAC Nov. 30, 6). Oregon also included

into the account the earlier prioritization of K-12 employees, this delayed Oregon's opening date for vaccinating the elderly until February 7, 2021 (whereas California, which prioritized the elderly ahead of K-12 employees, was able to start vaccinating the elderly on January 13, 2021).

None of these differences matter from the theoretical point of view—since, out of all prioritized groups, only grocery workers act as central nodes that connect large segments of society.[37] None of the pseudo-treatment test dates are associated with prominent shifts in the slope of the trend.[38]

## Conclusion

Unlike epidemiological studies that rely on aggregated population-level measures (e.g., Bubar et al. 2021), network science provides a more nuanced localized understanding of contagion in various types of network structures. Network tools allow for developing a more targeted and efficient approach to reducing contagion by focusing on the nodes with various transmission properties. This study demonstrates that using insights from network analysis to inform vaccine prioritization plans may have substantial effects on reducing contagion, and by implication, hospitalizations, and mortality rates.

While highly effective as a means to reduce transmission, onset, symptoms, and mortality, Covid-19 vaccines have proven to be heterogeneous in their effectiveness. In particular, they are the least effective for individuals that face the highest risk of adverse effects from the virus, such as the immunocompromised and the elderly. Somewhat counter-intuitively, this

several additional groups, such as individuals with developmental disabilities, employees of early learning centers, and individuals working in death care services (OVAC Jan. 14, 2021).

[37]In network analysis terms, K–12 employees and the incarcerated are cliques—network clusters with large numbers of repeat interactions, but few new ones.

[38]One caveat is that statistical analysis do not allow for isolating the effect of grocery employees from that of other food and agriculture workers, as all three of these groups were included on the same "agriculture and food" in both states. In technical terms, this means that the estimated effect is a "bundled" effect. Theoretically, agricultural workers or restaurant employees (e.g., short-order cooks) have similar network positions to teachers and the incarcerated—they interact primarily with other members of their own professional setting, but are relatively isolated from the general public, especially as a result of pandemic-related indoor dining bans. The placebo tests show no discernible effects for the incarcerated or K-12 educators, which implies that the treatment effect is driven by the grocery employees rather than other groups that happened to become eligible at the same time.

study demonstrates that the most effective strategy to protect these groups may be indirect. Rather than directly allocating the vaccines to the individuals for whom these vaccines are the least effective, it may be more efficient, under conditions of vaccine scarcity, to minimize the probability of these individuals' exposure to the virus by innoculating their most frequent contacts. Allocating scarce vaccine resources to the individuals that act as central nodes in the network of human interactions—such as grocery workers—may be a more effective means to reducing community spread and a more effective means at protecting the most vulnerable.

Outside of the specific application to Covid-19, this article has implications for studies using insights from network science. Now that network analysis became commonplace for studying political processes, the next step is to move from correlational to causal network analysis, and this paper takes a first step. Theoretically, it offers a number of testable implications for the study of diffusion more broadly, such as information cascades, diffusion of policy innovations, political mobilization, and contagion of political violence. For instance, targeting the central nodes in a network of information transmission is key to controlling the spread of information, such as misinformation, radical speech, or anti-regime rhetoric. The reverse strategy—structuring the network so as to ensure multiple transmission pathways, rather than relying on a small number of central nodes—is key to maintaining communication despite attempts at disruption, such as governments' attempts at censorship. Likewise, if the goal is to encourage the spread of policy innovation, from treaty ratification to regime change, then a focus on a small number of central nodes—key innovators—may be more cost-efficient than individual targeting of the entire pool of potential adopters. Similarly, advocacy groups may get a better return on investment by focusing on a handful of influential actors, rather than allocating resources across a wide set of government actors. This may hold for specific agencies within governments, as well.

Beyond the focus on network centrality, political science research can also explore other types of network dependencies, such as indirect ties or the average length of the shortest paths (e.g., Chyzh 2016). For example, and related to the previous point, advocacy groups may not want to focus solely on actors that are central in the entire network, but also on actors that may cause a tipping point that connect otherwise disconnected network clusters. Explicitly modeling known dependencies among political actors, and testing their implications within a causal network framework adds nuance to established political science findings.


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## Biographical Statement

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# Online Appendix for 'How to Stop Contagion: Applying Network Science to Evaluate the Effectiveness of Covid-19 Vaccine Distribution Plans'

Olga V. Chyzh*

April 13, 2023

## Appendix A: Definitions of Centrality Metrics

Formally, define the nodes in a network as a set of $n$ actors $i \in \{1, 2, \dots, n\}$, and one or more interactions between each pair of nodes $i$ and $j$ as a link, $l_{ij} = 1$. *Degree* is simply the total number of links for each node, or $\sum_{j:j\neq i} l_{ij}$. *Eigenvector centrality* is a more sophisticated analog of degree centrality, discussed in the article, that assigns higher values to nodes that are connected to other central nodes in the network.A node's eigenvector centrality, $c_i^e$ is calculated as $c_i^e = \lambda^{-1} \sum_{j:j\neq i} l_{ij} c_j^e$, where $\lambda$ is the largest eigenvalue of the adjacency matrix that represents a given network. Next, if we define $d_{ij}$ as the shortest path between $i$ and each other node $j$ in the network,[1] then each node's *closeness centrality* is the inverse of the sum of the shortest paths that separate each node from all other nodes, or $\frac{1}{\sum_{j:j\neq i} d_{ij}}$ (Bavelas 1948). Finally, for all pair of nodes $j$ and $k$, we can define the number of shortest paths between them as $g_{j,k}$. Then, for each node $i$, we can define *betweenness centrality*, $g_{j,k}(i)$, as the number of the shortest paths $g_{j,k}$ that go through $i$ (Freeman 1977; Padgett and Ansell 1993).

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[1]If $i$ and $j$ share a link, the shortest path $d_{ij}$ is equal to 1; if $i$ and $j$ are not directly connected, but are each connected to a third node $k$, then the shortest path $d_{ij} = 2$, and so on.

## Appendix B: The Simulation

Consider the canonical interaction data for 73 boys in a small high school in Illinois in Spring 1958 (Coleman 1964). In this network, two individuals are connected by a link if at least one of them named the other in response to the question "What fellows here in school do you go around with most often?"[2] Links in this network are measures of frequent elective interactions among individuals, which makes these data a perfect fit for deriving predictions related to contagion and the strategies of its containment. Figure 1 shows the distributions of individuals' degree, closeness, betweenness, and eigenvalue centrality measures in these data.

In Figure 2, the node with the second highest value on each centrality measure is shown in dark red.[3] Without loss of generality, assume that the virus spreads on contact with certainty. If the dark red nodes are the initial carrier (Patient 0), then its direct neighbors (shown in red) are next catch the virus, after which the virus spreads to the nodes that are reachable through a shortest path of length 2 (shown in orange) as a part of the second round. The figure shows that the choice of Patient 0 has substantial implications for contagion speed and pathways. Counter-intuitively, in this example, infecting the node based on degree centrality does not lead to the largest number of infected individuals at the end of two rounds. The scenarios with the highest rate of infected are the ones in which Patient 0 is chosen based on maximizing betweenness centrality (38 infected) and closeness centrality (36 infected).

Since the local structures in the network affect contagion's speed and reach, we can leverage these structures to reduce contagion. Suppose there are 10 available vaccines. Without loss of generality, assume getting a vaccine makes an individual both immune to the virus and unable to transmit it.

[2] I transformed the original directed network data into a non-directed symmetric network.

[3] The same node happens to get the highest score on all four measures on centrality discussed here. To introduce variation into the demonstration, I therefore chose to show the node with the second highest value on each centrality measure.

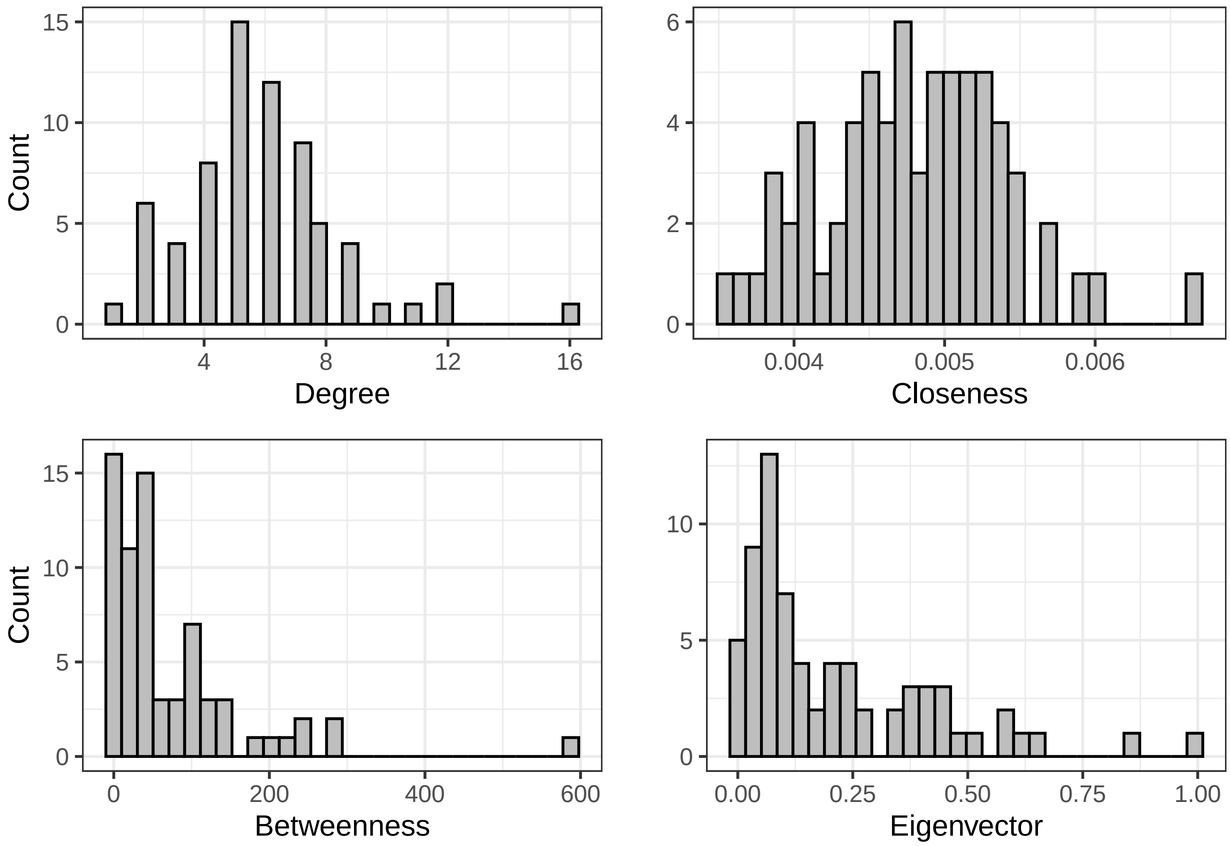


Figure 1: Centrality in the Interaction Network

Figure 3 shows the spread of the virus under five vaccination scenarios:

1. *Low Degree Scenario*—distribute vaccine to the nodes with the lowest degree centrality;
2. *High Degree Scenario*—distribute vaccine to the nodes with the highest degree centrality;
3. *High Closeness Scenario*—distribute vaccine to the nodes with the highest closeness centrality;
4. *High Betweenness Scenario*—distribute vaccine to the nodes with the highest betweenness centrality;
5. *High Eigenvector Scenario*—distribute vaccine to the nodes with the highest eigenvector centrality.[4]

The *Low Degree Scenario* scenario mimics the strategy of prioritizing vaccinations by

[4]In case of a tie, I randomly choose nodes with the same centrality until I reach the required number.

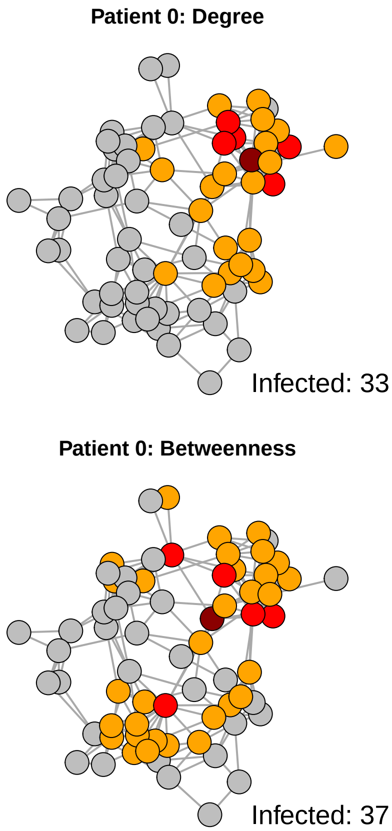


Figure 2: Contagion in the Interaction Network

mortality risk. In practice, this strategy focused on introducing vaccines by age groups, starting with the oldest. By defining *vulnerable individuals* as those with the lowest degree centrality, I assume that these are high-risk individuals who chose to limit their risk of exposure by reducing their number of social interactions (i.e., they are willing and able to do so).[5]

The *High Degree Scenario* scenario may be thought of as one, in which vaccine priority goes to individuals with the highest number of face-to-face interactions. These individuals include essential frontline workers, such as medical staff, post office employees, and individuals employed at pharmacies or grocery stores.

The differences between the categories of individuals that would be prioritized under the

[5]The network science focus of the study limits our insights to groups of individuals that are identifiable as a function of their network connections. Making separate inferences for vulnerable individuals that are either unable or unwilling to self-isolate by reducing their number of direct contacts are treated as beyond the scope of this article.

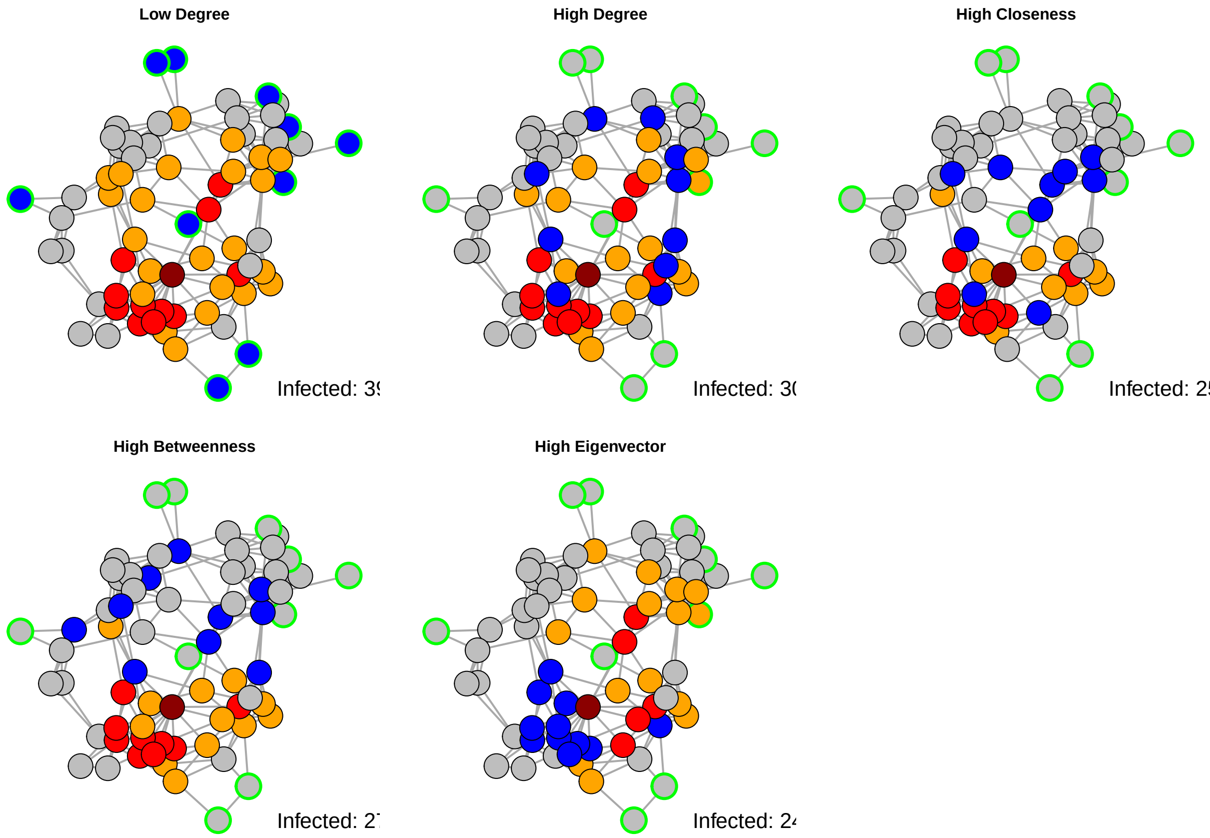


Figure 3: Vaccination Scenarios

three remaining scenarios are less obvious. Under the *High Closeness Scenario*, the vaccine priority would go to individuals that are reachable by every other individual in the network though the smallest number of contacts. These individuals may include a subset of essential employees, such as doctors and nurses. Under the *High Betweenness Scenario*, vaccination would start with the individuals that are most important for connecting the network, such as grocery workers, nurses that work at multiple hospitals, or care-takers that work at multiple retirement communities. The *High Eigenvector Scenario* would prioritize vaccinating clusters of individuals who all engage in large numbers of face-to-face interactions. Such individuals may include essential frontline workers that service group living communities, such as retirement homes or college dorms.

In order to make comparisons among these scenarios, I designate Patient 0 as the node with the highest scores on all centrality measures. Since, by definition, nodes with no connections cannot be infected by contact, I remove these from the network prior to the simulation. The demonstration shows that all but the first vaccination scenario leads to a drastic reduction of contagion in the network. Compared to the first vaccination scenario, vaccination scenarios 2–5 help reduce contagion after the second round by anywhere between 9 and 14 cases of infection. In a network of 69 individuals (after removing the isolates), this is a difference between infecting 57 vs. only 29–36 percent of the nodes in the network.

If we think of the nodes with the lowest degree centrality (marked with green border color in the figure) as vulnerable individuals, this demonstration also shows that all of the vaccination scenarios fare extremely well at protecting these individuals. Only 1 such node gets exposed to the virus in two of the scenarios.

As stark as these results may look, they are based on analyzing a single real-world interaction network, and therefore provide no insights regarding the uncertainty around the estimates of infection rates. To estimate the uncertainty around the estimates, I perform the following Monte Carlo experiment. I start by estimating an exponential random graph model (ERGM) (Wasserman and Faust 1994), in which the interaction network is the dependent variable, and the network parameters of interest are the baseline link probability (*edges*), the tendency towards open triangles (*2-stars*), and closed triangles (*gwesp*).[6] The estimates of this model are shown in Table 1.

Table 1: ERGM Fit of the Interaction Network

| | | |
|---|---|---|
| Edges | -3.72 | 0.36 |
| k-Star(2) | -0.14 | 0.03 |
| Gwesp (decay=0.5) | 1.98 | 0.16 |

I then use the estimates from this model to simulate the interaction network 10,000 times, and repeat the analysis done on the original interactions network on these simulated networks.[7] Table 2 and Figure 4 provide summaries of these simulations.

[6]ERGMs are an estimation approach for modeling the probability of observing a network with a given set of endogenous statistics, such as the total number of edges, open or closed triangles, or other network features (Hunter et al. 2008; Robins et al. 2007).

[7]For a similar simulation approach, see Boehmke et al. (2017).

Table 2: Round 2 Summary for 10,000 Simulations of the Interaction Network among 73 Individuals

| | Vaccinated | Infected | Not Infected | Vulnerable Infected |
|---|---|---|---|---|
| No Vaccine | 0 | 39.35 (5.40) | 28.65 (5.40) | 3.24 (1.51) |
| Low Degree | 10 | 36.04 (5.07) | 21.96 (5.07) | 0 |
| High Degree | 10 | 24.13 (4.74) | 33.87 (4.74) | 2.38 (1.38) |
| High Closeness | 10 | 22.41 (4.61) | 35.59 (4.61) | 2.38 (1.36) |
| High Betweenness | 10 | 24.69 (4.66) | 33.31 (4.66) | 2.21 (1.30) |
| High Eigenvector | 10 | 22.10 (6.02) | 35.90 (6.02) | 2.39 (1.44) |

*Note:*
Cell values are means over 10,000 simulations. Numbers in parentheses are standard deviations. *Not Infected* does not include *Vaccinated*.

Table 2 shows the mean (standard deviation) of the number of individuals infected/not infected after the second round of contagion (individuals connected to Patient 0 directly or via one intermediary) in 10,000 simulations of the interaction network. Just as before, I denote the 10 individuals with the lowest number of direct (lowest degree centrality) connections as the "vulnerable" individuals. These are the individuals vaccinated in the *Low Degree* scenario. The last column of Table 2 shows the mean (standard deviation) for the number of these individuals that are infected under each of the vaccination scenarios. I also perform a simulation for the *No Vaccine* scenario as a reference for comparison.

Under the *Low Degree* scenario of giving vaccine priority to the vulnerable individuals, the number of individuals infected after the second round is only slightly lower than that under the *No Vaccine* scenario (roughly 36 vs. 39). Under each of the alternative scenarios, the number of infected is substantially lower both in absolute terms and as a percent decrease. In absolute terms, any of the alternative vaccination scenarios reduce the number of infected individuals by between about 11 (*High Betweenness*) and 14 individuals (*High Closeness*). Accounting for the overall size of the simulated networks, these are the differences between protecting only 46 percent of individuals in the network (31 out of a total of 68 individuals are vaccinated or not infected) in the *Low Degree* scenario and 65 percent in the *High Closeness* or *High Betweenness* scenarios.

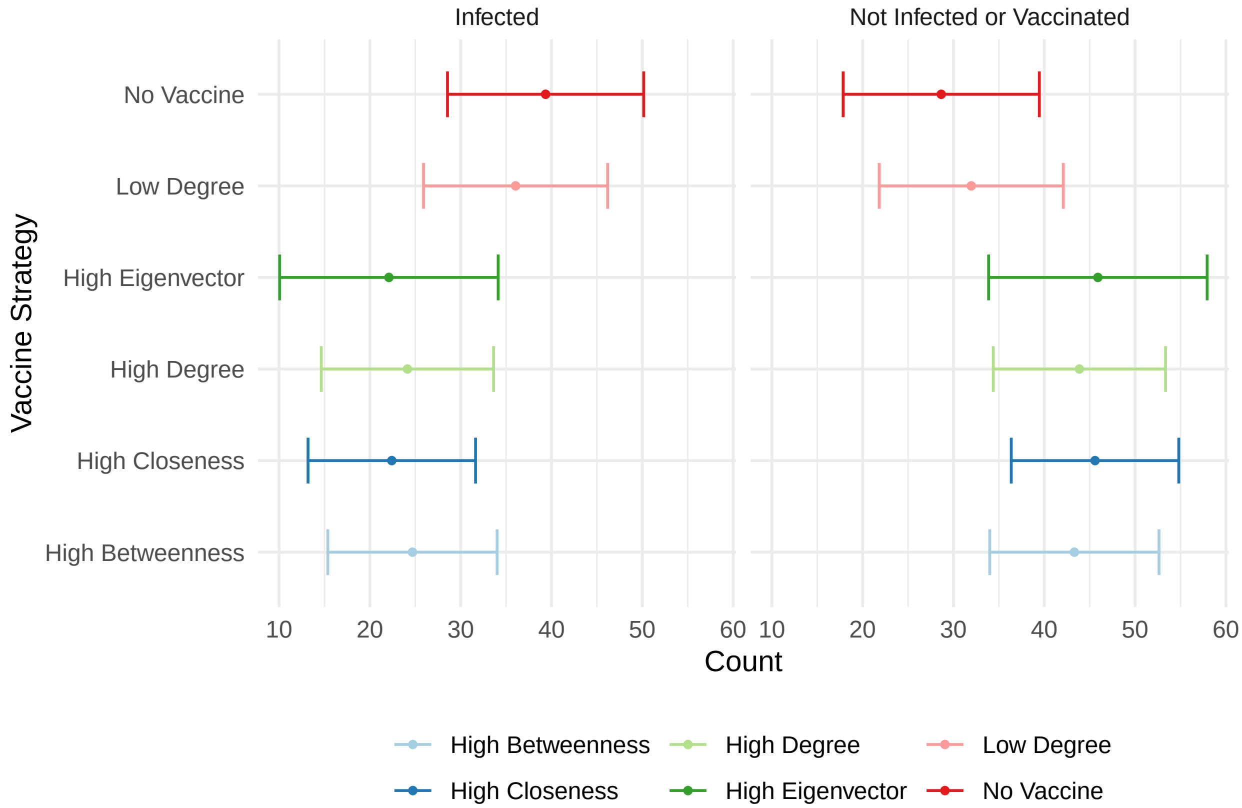


Figure 4: Average Infection Rates over 10,000 Simulations

Among the four high centrality-based vaccination scenarios, the spread of infection is minimized under the *High Eigenvector* scenario, although the differences are not very large. The *High Betweenness* scenario is the least efficient at reducing the spread of the infection.

Importantly, under all but the *Low Degree* scenario, a small number of vulnerable individuals (fewer than 2.5) are infected. A rather significant reduction in the spread of infection, therefore, comes at a price of failing to protect a small number of vulnerable individuals, though this number is still smaller than under the *No Vaccine* scenario.

Figure 4 provides a visual summary of the same results. The first subfigure shows the infection rates for each scenario, whereas the second subfigure shows the combined numbers of individuals that are not infected or vaccinated. We can again see that the *Low Degree* strategy leads to the outcome that is very similar to that of *No Vaccine*, whereas all of the alternative scenarios lead to substantial decreases in virus spread.

### Relaxing Assumptions: Network Cliques, Risk of Exposure, and Probability of Transmission

The main argument—that vaccinating public-facing essential employees is key for reducing contagion among the public—holds even for individuals with the highest vulnerability to the virus due to age or living arrangements. From a network perspective, the elderly individuals residing in nursing homes—the group with the highest Covid-19 death rates—are a network clique—a network component in which every individual comes in contact with every other individual.[8] The property of a clique—and a partial reason of the high pandemic death rates in nursing homes—is that infection of a single member poses a disproportionately high risk of infection of the entire clique. Under the conditions of vaccine scarcity—that is, assuming there is not enough vaccine to inoculate every member of the clique—the highest risk for the clique comes not from its members, but from its members' contacts that are external to the clique. Members of cliques rank high on *degree*, but not on *betweenness centrality.* The best way to protect the clique, therefore, is to limit its members external contacts to only the most essential ones, such as food and medical service providers. Interaction with essential service providers—the one contact that cannot be severed—however, also poses the highest risk of contracting the virus, as previously shown. This means that, once again, inoculating essential workers is key to protecting vulnerable individuals in congregate work- or living arrangements. The bottom line is that, as long as the vaccine is too scarce to inoculate every member of a clique, the best protection is to protect those who are indispensable for the cliques' functioning—medical workers and public-facing essential workers. This implication is even stronger given that, as we now know, the Covid-19 vaccines' effectiveness declines with individuals vulnerability (Andrews et al. 2021; Nunes et al. 2021; Salmeron Rios et al. 2022).

Buckner, Chowell, and Springborn (2021), for instance, use a simulation to show that, if the goal is to minimize deaths, the strategy of vaccinating the elderly is optimal only if we

[8]Other examples of network cliques are in-person classrooms, prisons, and dormitories.

can assume that the vaccine is at least 90 percent effective for everyone in the population. If vaccine effectiveness for the vulnerable populations, such as the elderly, drops to 50 percent, then prioritizing essential workers has a greater effect on reducing both deaths and spread.

To briefly demonstrate using the methods employed here, Figure 5 shows a hypothetical network. Scenario 1 illustrates the structure of this network prior to Covid-19 exposure. The network consists of two cliques (shown in gray), two essential workers that service these cliques (shown in green), as well as other individuals (shown in white). One can imagine such a clique nested within a broader network.

Scenario 2 demonstrates the spread of the virus, should one of the essential employees (dark red) contract the virus.[9] In the first round of contagion, the virus spreads to all of the members of the general public who come in contact with the exposed individual (those infected in the first round are shown in red), as well as one member of each of the cliques that consist of the vulnerable individuals. During the second round of contagion, all members of both cliques contract the virus (those infected in the second round are shown in orange).

Scenario 3 shows the same scenario, but assuming that five of the randomly selected vulnerable individuals are vaccinated (shown in blue). In the first round of contagion, the virus spreads to two of the unvaccinated vulnerable individuals who happen to interact with the essential worker. In the second round of contagion, the virus spreads to the rest of the cliques, save for the vaccinated individuals.

Scenario 4 shows the same scenario, but now the scarce vaccines are given out based on the total number of contacts (degree centrality). Now, if the essential worker—Patient 0 from the previous scenarios—is vaccinated, then nobody is infected. Since vaccines are not 100 percent effective, however, we may assume that Patient 0 is a breakthrough case—they get infected, despite being vaccinated. We can see, however, that vaccinating based on the number of contacts still ensures the protection of the two cliques. Since the individuals who come in contact with the essential worker are also prioritized under this scenario, they

[9]This individual has the highest risk of contracting the virus, given their large number of interactions.

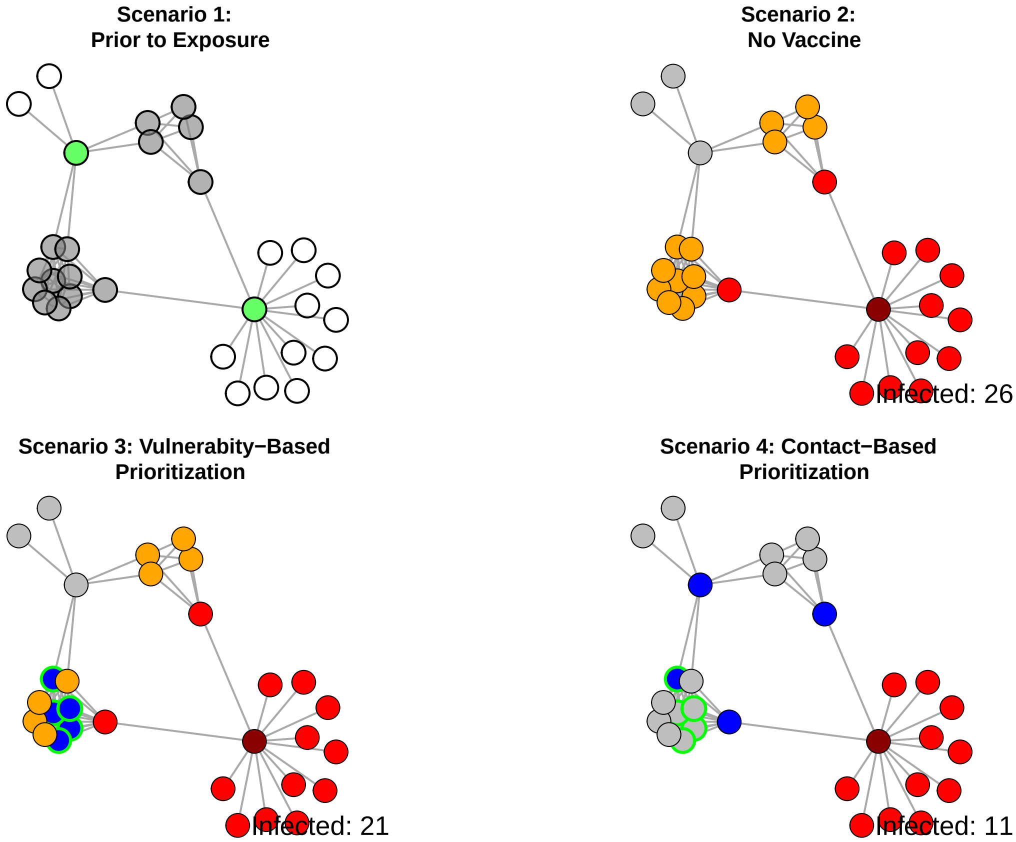


Figure 5: Virus Spread in Networks with Cliques

prevent the spread of the virus to their cliques.

The assumption in the simulations is that the virus spreads on contact with certainty. The manuscript's results, therefore, apply to the worst case scenario. Should we relax this assumption—that is, assume that the virus spreads on contact with some probability $p < 1$, the main results still hold. No matter the probability of spread, individuals are still most likely to contract the virus from the people they see the most *and* individuals with the highest centrality are still the most likely to contract and spread the virus. The same implication holds under increased risk of exposure, for example, if some individuals are unwilling or unable to social distance or wear masks.

The same logic applies to the assumption regarding vaccine's effectiveness. If the vaccine is less than 100 percent effective, then prioritizing vaccine access based on centrality is even more essential, as is demonstrated in the Scenario 4 of Figure 5. Should the essential employee contract the virus, despite being vaccinated, vaccinating their contact person in the clique (e.g., the concierge who accepts deliveries) is key for protecting the rest of the clique's members (e.g., long-term care residents for whom the vaccine is the least effective).

## Appendix C. Vaccine Prioritization at the National Level

Table 3 shows the chronological order, in which the states opened up vaccine access to grocery employees. The table shows that both Republican- and Democratic-led states appear throughout the timeline.

Table 3: Grocery Eligibility Dates by State

| Date | States |
|---|---|
| Jan 08 | New Mexico |
| Jan 11 | New York, Virginia |
| Jan 20 | Nebraska* |
| Jan 21 | Kansas |
| Jan 25 | Illinois, Maryland* |
| Feb 08 | Alabama* |
| Feb 18 | District of Columbia |
| Feb 24 | Wyoming* |
| Mar 01 | California, Kentucky, Wisconsin |
| Mar 02 | Nevada |
| Mar 03 | Alaska*, North Carolina |
| Mar 05 | Colorado |
| Mar 08 | Arkansas*, North Dakota*, South Carolina* |
| Mar 09 | Oklahoma* |
| Mar 10 | Minnesota |
| Mar 15 | Hawaii, Idaho*, Missouri* |
| Mar 16 | Mississippi*, West Virginia* |
| Mar 17 | Washington |
| Mar 22 | Louisiana, Massachusetts*, Oregon, South Dakota* |
| Mar 24 | Arizona*, Utah* |
| Mar 25 | Georgia* |
| Mar 29 | New Jersey, Ohio*, Texas* |
| Mar 31 | Indiana* |
| Apr 01 | Montana* |
| Apr 02 | New Hampshire* |
| Apr 05 | Connecticut, Florida*, Iowa*, Michigan, Tennessee* |
| Apr 06 | Delaware |
| Apr 07 | Maine |
| Apr 12 | Pennsylvania |
| Apr 19 | Rhode Island, Vermont* |

* Republican-governed states.

To further explore the effect of demographic and political factors that may have influenced vaccine prioritization, I estimate two Cox survival models of time to eligibility for (a) grocery employees, and (b) individuals aged 65 and above for all US states. A Cox survival model is appropriate because both groups became eligible at some point in all states, as all states eventually opened vaccine eligibility to the general public. If partisan politics were at play, we would expect that the timing of vaccine eligibility would systematically correlate with the size of politically active demographic groups. For example, we may see grocery workers receive lower priority in states with higher median age, and vice versa: states with higher median age would give earlier priority to individuals aged 65 and above.

Table 4 presents the results. The only variable that has a statistically significant effect in Model 1 is *Urbanization*. This effect, however, is in the direction opposite to what one would expect based on partisanship: states with higher level of urbanization took longer, on average, to open vaccine eligibility to grocery employees. *GDP/capita* is significant at an $\alpha = 0.1$ level, which suggests that states with higher administrative capacity were quicker to open vaccine eligibility to grocery employees. This difference is accounted for in the main analysis via matching and statistical control.

Several variables have statistically significant effects on time to eligibility for individuals aged 65 and older in Model 2. First, just like in the model of grocery employee eligibility, *GDP/capita* has a positive and statistically significant effect at $\alpha = 0.1$. This indicates that the effect of capacity is at work for the general pace of vaccination—states with higher capacity were, on average, faster at opening vaccine eligibility for both individuals aged 65 and older and grocery employees. *Unemployement Rate* is negative and statistically significant, which indicates that states with higher unemployement levels were slower to open vaccine eligibility to individuals aged 65 and older. *Biden's Margin* is negative and statistically significant, which suggests that, on average, more Democratic states were slower at vaccinating individuals aged 65 and older. Finally, *Percent Black* and *Percent Latin* are positive and statistically significant, which indicates that states with larger minority

Table 4: Determinants of Eligibility Date for Grocery Employees and Individuals Aged 65 and Over

| | Grocery | | Age 65 Plus | |
|---|---|---|---|---|
| GDP/cap | $0.026^{\dagger}$ | (0.015) | $0.028^{\dagger}$ | (0.015) |
| Median Age | −0.148 | (0.123) | 0.131 | (0.150) |
| State Population, logged | 0.034 | (0.540) | $1.563^{*}$ | (0.694) |
| Unemployment Rate | 7.611 | (11.155) | $-18.459^{\dagger}$ | (10.738) |
| Percent BA Degree | 9.986 | (13.493) | −0.867 | (11.189) |
| Grocery Employees/100 | −1.315 | (1.480) | −1.551 | (1.505) |
| Republican Governor | −0.752 | (0.463) | 0.078 | (0.371) |
| Biden's Margin | −0.782 | (1.839) | $-3.636^{\dagger}$ | (1.880) |
| Urbanization | $-3.156^{*}$ | (1.466) | −1.263 | (1.821) |
| Percent Latin | 3.027 | (2.296) | $4.255^{\dagger}$ | (2.478) |
| Percent Black | 0.402 | (2.545) | $7.096^{**}$ | (2.627) |
| Cum. Covid-19 Cases, logged | 0.138 | (0.556) | −0.482 | (0.559) |
| Num.Obs. | 51 | | 51 | |
| $R^2$ | 0.359 | | 0.354 | |
| Log.Lik. | -141.085 | | -141.257 | |

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$ $^{\dagger}p < 0.1$.

populations were faster at vaccinating individuals of age 65 and over.

These results provide a comparison between the factors that are correlated with vaccine eligibility dates for the two groups. It is worth noting that, as the case studies will later show, on January 12, 2021, the CDC issued a change to its initial recommendation, urging all states to vaccinate individuals 65 and older as soon as possible. Both California and Oregon reacted to these revised guidelines by including individuals 65 and older in Phase 1b, along with, or ahead of, the next scheduled priority groups; most other states did the same. This means that the dependent variable in Model 2 of Table 4 is essentially a proxy for the general rate of vaccination in each state: states that were further along in their Phase 1a as of January 12 were able to open eligibility for individuals of age 65 and over soon after the change in the guidelines.

In comparison, the lack of statistical significance on the coefficients in Model 1, however, highlights two broader points: (1) that the decision to prioritize grocery employees was not driven by partisan considerations, and (2) that the timing of grocery employee eligibility is not well explained at a systematic level. That is, save for state capacity, the timing of vaccine eligibility for grocery workers is driven by idiosyncratic factors.

## Appendix D. Unconfoundedness: An Analytical Justification

Analytically, ruling out unit self-selection consists of showing that observations were not assigned to treatments based on a confounder—an unobservable variable that also affects the outcome of interest.[10] This requires demonstrating that the treatment and the control groups are similar, on average, on any observed and unobserved variables that may affect the outcome of interest. Or, to put it another way, that units that received that treatment only did so as a result of unsystematic idiosyncratic factors that have nothing to do with the features of the units themselves. And were the experiment to be repeated, it is quite likely that the units that received the treatment would have been assigned to the control group, and vice versa.

In contrast, a case of non-random unit assignment to treatments—the dreaded selection effect—would be observed if the observations were assigned to the treatment and control groups based on some unobservable characteristic that also affects the outcome. The classic example of such an assignment mechanism is a doctor using their medical expertise to prescribe their patients the drugs that will help best treat their symptoms. In the current application, the role of the doctor is played by the governor's office, and the corresponding selection process would consist of tailoring the vaccine priority plan to the demographics of the state.

To understand which of the assignment mechanisms were at work in this particular application, I conducted case studies of the decision-making processes in each state by studying the records (minutes from meetings, meeting summaries, slides, video recordings, and other materials) made available by the California and Oregon vaccine advisory committees (CVAC

[10][T]he unobserved differences that lead to differences in treatments need not lead to violations of unconfoundedness" (Imbens and Rubin 2015, 265). That is, unconfoundedness still holds, as long as the unobserved differences that resulted in unit assignment to the treatment/control conditions "are independent potential outcomes, conditional of observed covariates" (Imbens and Rubin 2015, 265). Imbens and Rubin (2015) (265) give an example, in which a doctor assigned patients to drug A vs. drug B based on the costs covered by patients' insurance plans. As long as the patients purchased their insurance prior to their diagnosis, we would not expect insurance benefits to be correlated with which drug is best for treating each patient.

and OVAC, respectively),[11] as well as contemporaneous news stories and press releases. The case studies are presented in full in Appendix E.

Specifically, I studied the materials taking note of any evidence of:

1. Available information: Did the governors' offices or the health officials believe that vaccine prevented transmission of the virus and/or acted on this belief in making prioritization decisions? If such evidence were available, or if the health officials acted on an assumption that it will become available later, that would make it more likely that the health officials may have formulated vaccine priority plans so as to minimize transmission in their state. This would indicate that the treatment assignment mechanism could affect the outcome variable (Covid-19 case counts). Such evidence would, therefore, weaken the justification for the unconfoundedness assumption.
2. Deviations from national guidelines: Did the governors' office or the health officials believe to have information on what prioritization plan would work best for their state's demographics? If the decision-makers had this information, they could use it to tailor the vaccine priority list to their local context, which would be evidence against unconfoundedness. Such evidence would include, for example, arguments for modifying the national guidelines in the view of differing local data on hospitalizations, mortality, etc.
3. Random shocks: Was the decision-making affected by any exogenous events (events beyond the governor's control)? If I find evidence that vaccine priority lists were formed as a result of exogenous shocks rather than concerted efforts by the governor's office, this would increase the credibility of the exogeneity assumption.

[11] California materials are available from https://www.cdph.ca.gov/Programs/CID/DCDC/Pages/COVID-19/Community-Vaccine-Advisory-Committee.aspx, Oregon materials are available from https://www.oregon.gov/oha/ph/preventionwellness/vaccinesimmunization/immunizationpartnerships/pages/covid-19-vaccine-advisory-committee.aspx.

**Available Information**

A systematic correlation between the treatment assignment and the outcome—assigning a patient to the treatment that is the most beneficial—requires that the doctor has expertise in treating the given disease, i.e. has a reasonable expectation of what is the best treatment for each patient. If patients are assigned to treatments by a snake doctor rather than a medical doctor, then the assignment mechanism is not that different from tossing a coin or rolling a die. In other words, an uninformed decision-maker approximates a randomization mechanism.

To assess the level of information available to the decision-makers at the time of vaccine prioritization, I studied the materials made available by California and Oregon vaccine advisory committees. The evidence indeed suggests that the key decisions were made under low levels of information and moderate degree of uncertainty. California's health authorities had emphasized the lack of information on vaccine effectiveness at preventing any outcomes other than severe disease at the early stages of the planning (meetings between November 25 and December 16). For example, in the November 30 meeting, the health officials pointed out that:

"[...] there is no data to show that the vaccine prevents transmission, so decisions are being made based on criticality to societal functioning plus long-term residents because of their disproportionate mortality burden. We therefore can't yet direct vaccine to help prevent further transmission (CVAC Nov. 30, 2020, 13).

The January 12 recommendation of California's Drafting Guidelines Workgroup—a committee of medical officials that was directly tasked with developing the vaccine prioritization plan—notes:

"[...] recommendations reflect that, at the time of initial availability, evidence will indicate that COVID-19 vaccine protects against COVID-19 disease. Evidence of the vaccine's impact on COVID-19 mortality will likely follow. However, current evidence is too limited as of December 2020 to determine whether or not the vaccine will protect against the spread of SARS-CoV2 infection to others" (CDGW, Jan. 12, 2020, 1).

Having established this early on, the committee deliberations included no discussion of vaccines ability to prevent transmission *until the March 17 meeting*, in which the health officials reported that the Johnson & Johnson studies produced evidence of their vaccine's effectiveness at preventing transmission (CVAC Mar. 17, 2020, 5–6).

This suggests that, at the time of the treatment assignment, on March 1, 2021, the decision-makers did not have enough information to self-select into a treatment that would rely on reducing disease transmission as the primary mechanism of achieving their primary goals of reducing hospitalizations and deaths.

Interestingly, Oregon's health officials were somewhat more optimistic regarding the vaccine's ability to prevent transmission, even early on. In the January 7 meeting, a representative of Oregon Health Authority said, for example:

"While this vaccine very likely reduces transmission to some degree, we don't actually have current data saying how much and to what extent. So this can be a secondary consideration, because we do believe that the vaccine will probably limit transmission to some degree, but this is not something that we can confidently say as much as preventing the person who gets vaccinated from getting sick" (OVAC, Jan. 7, 2021).

As evident by Oregon's vaccine priority plan, however, this confidence did not seem to translate into a plan to prioritize groups based on their transmission potential: Oregon makes up the placebo group in this study, as its grocery employees were prioritized on a later timeline than California. The possible reasons for this will become more apparent in the next two subsections.

In summary, the evidence so far is by no means definitive, but does provide some initial justification for making the unconfoundedness assumption.

**Deviations from National Guidelines:**

A critique of the above argument is that committee deliberations may not reveal the full picture. It is possible, for example, that the governors were using the committees to create an appearance of an inclusive decision-making process, while in actuality, the vaccination plan was pre-determined based on some specific goal, such as to buy off political support. This would undermine the justification of unconfoundedness on the grounds of an uninformed decision-maker. Instead, it would suggest that the assignment was performed by an informed decision-maker with an unknown agenda.[12] If the decision-maker (the governor's office) had a pre-determined agenda, then there should be instances, in which the health authorities advocate for and implement deviations from the national vaccine priority guidelines. I searched the committees' materials for evidence that would support such a process.

The starting point for prioritization within Phase 1a was each state's interpretation of the CDC guidelines to prioritize (1) healthcare workers, such as EMTs and paramedics; and (2) other essential workers, including law enforcement and fire safety (CVAC Nov. 25, 2020, 9). Materials from both states' committees indicate an intention to adhere to the national guidelines. In the November 25 meeting, California health officials stated that "[they] plan to start from the NASEM framework and national recommendations. We would want a strong rationale for California to deviate from these guidelines" (CVAC Nov. 25, 2020, 5). At the same time, it was also acknowledged that the goal of the vaccine advisory committee was to "customize federal guidelines to California" (CVAC Nov 25, 2020, 5).

With the two stated goals seemingly at odds, one can evaluate the relative importance of each by analyzing the instances of disagreements. For example, in the November 30 meeting, the health officials noted that the plan was to include Phase 1a priority for residents of skilled nursing facilities, assisted living facilities, and other long-term care settings (CVAC Nov 30, 2020, 5). It was clarified, in response to a question, that:

[12] The statistical analysis, presented in Appendix C and discussed in the article, already showed no evidence of a political process, in which the governors sought to reward their supporters. Here, I perform additional qualitative analysis to further validate those results.

"If the ACIP [the CDC Advisory Committee on Immunization Planning] does not include nursing home residents, we would carefully consider whether they fit in Phase 1a or Phase 1b. We prefer to align with national recommendations wherever possible but would consider alternatives if justified" (CVAC Nov 30, 2020, 12)

California's willingness to over-ride the federal guidelines on this matter did not come to the test, as the ACIP guidelines did include the above-mentioned groups.

Another example of how California's plan fit within the national guidelines is the parallel drawn by the health officials in the December 23 meeting:

"There is a great deal of overlap between the ACIP proposal and the thinking thus far by the Drafting Guidelines Workgroup. One difference is that ACIP is recommending additional frontline workers that California initially did not include: Manufacturing, Postal Service and Public Transit, as well as persons 75 years and older. California's Drafting Guidelines Workgroup has been considering other high-risk groups not been proposed by the ACIP" (CVAC Dec 23, 2020, 6).

In this case, California stood by its own plan, at least initially: in a January 4, 2021, press conference, Governor Newsom announced that, per committee's recommendations, Tier 1 Phase 1b—set to open on January 13, 2021—was to include individuals of age 75 or older, educators and childcare workers, emergency service employees, and individuals employed in food and agriculture (Newsom 2021).[13]

For the case of Oregon, an early deviation was to intentionally define its Phase 1a priority category as "more inclusive than other states to include behavioral health, intellectual and physical disabilities (and people who support them), interpreters, outpatient settings, food servers, and cleaners in hospitals" (OVAC Jan 14, 2021, 9:04).

The real test of each state's willingness to over-ride the national guidelines, however, happened in the form of a sudden change in the CDC guidelines that took place on January 12. Announced with no advanced notice to the states, the new guidelines were to use age

[13]That is, California included some, but not all of the ACIP-recommended occupational groups.

as the primary criterion for prioritizing vaccinations and to expand eligibility to individuals aged 65 and over as well as people 16–65 with pre-existing medical conditions. This new recommendation was motivated by the disproportionate numbers of hospitalizations, ICU admissions, and deaths among the individuals in these groups (CVAC Jan. 12, 2021, 3; Brown 2021b). This change, of course, was a reversal on the previous guidelines that emphasized both age and the risk of exposure as the primary criteria for vaccine prioritization.

Both states responded to this change in guidelines in the exact same way—by modifying their vaccine prioritization lists so as to include individuals 65 and older. In Oregon, Governor Kate Brown announced the change in the CDC guidelines and her decision to include this group in the Phase 1b, in the same press conference on January 12 (Brown 2021). Such a quick reaction would have allowed little time for consultation with state health officials. This indicates a preference for adhering to the federal guidelines rather than tailoring the federal recommendations to local conditions—evidence against state self-selection into most favorable vaccine prioritization strategies. Indirectly, the decision to deviate from the previously announced plan also strengthens the low-information argument made in the previous section: had the states acted in conditions of higher certainty, they might have been less quick to deviate from their pre-established plans.

The addition of individuals 65 and older, together with the previous directive to prioritize K-12 staff and educators,[14] essentially pre-determined the composition of Oregon's Phase 1b, taking the decision-making out of the hands of Oregon's VAC that at the time was still in the information-gathering stage of the decision-making process. At the January 14 meeting of Oregon's VAC, the committee was informed of these changes.

Likewise, in an emergency meeting of the VAC, California's Department of Public Health (CDPH) agreed on expanding the previously announced Tier 1 of Phase 1b to include individuals of ages 65 to 74, in addition to previously defined groups. As a result, California

[14]Oregon's Governor Kate Brown announced her decision to prioritize K-12 educators and staff in the December 23 press conference. This announcement was consistent with the contemporaneous CDC guidelines to prioritize based on both age and occupational exposure (Botkin 2021).

began "the transition from an age- and sector-based approach to an age-focused approach to vaccine prioritization" (CVAC Feb. 3, 2021, 13). Combined with the already existing guidelines to sub-prioritize based on individual-specific factors, such as age, this transition effectively placed individuals aged 65 and older ahead of the rest of previously prioritized groups in Tier 1 of Phase 1b, such as childcare providers, educators, first responders, and employees of the agriculture and food sectors.

The decision to *expand* Tier 1 of Phase 1b, rather than to scrap the previously defined occupation-based prioritization altogether, stemmed from an equity consideration, as some smaller counties had already begun contacting individuals who had qualified as part of Tier 1 of Phase 1b prior to the change in guidelines (CVAC Feb. 3, 2021, 19). Once the new guidelines were announced, occupation-based prioritization was effectively suspended until the state was able to vaccinate the bulk of individuals aged 65 and older.[15]

On balance, both states' willingness to incorporate the change in the CDC guidelines, even if that meant altering the previously formulated plan, provides evidence against self-selection. Had the governors' offices held strong views on how to distribute the vaccine, given their states' political landscapes, we would expect to see reluctance to scrap or alter such plans in the face of new guidelines.

### Random Shocks

As the above description shows, the change in the CDC guidelines was an unexpected shock to the two states' prioritization processes. Prior to this change, California's health officials argued that whereas the data showed greater risks for individuals aged 75 and older, those aged 65-74 had a significantly lower risk and could be given a lower priority (CVAC Dec. 23, 2020, 10). In fact, California's committee recommendations formulated prior to the change

[15]The framing of this change as an *expansion* of Tier 1 of Phase 1b, when in actuality individuals aged 65 and older were effectively placed ahead of other groups within this tier, caused some confusion. In the February 3 meeting of CVAC, several members pointed out that the state online appointment system no longer allowed childcare, food and agriculture workers to sign up for vaccine appointments, despite the continued assurances from the CDPH that they were still a part of Tier 1 of Phase 1b (CVAC Feb 3, 2021, 16).

in guidelines, placed people aged 65 and older in Tier 2 of Phase 1b, behind individuals employed in education and childcare, emergency services, and food and agriculture (CVAC Jan. 6, 2020, 7).

While at the time of the change, Oregon was about two weeks behind California in the planning process, exposure-based prioritization was also a large part of the discussion in its committee. In the January 7 meeting, the OHA listed essential workers as the first out of three groups to be discussed as candidates for Phase 1b prioritization (along with individuals with high-risk medical conditions and individuals 65 and over) (OVAC, Jan. 7, 2021). While Oregon's committee did not reach the stage of making recommendations until after January 12, the information shared by the OHA in the pre-January 12 meetings, and the discussions that ensued, give no indication that Oregon's committee was set on age-based prioritization prior to January 12. Oregon Governor's decision to prioritize K-12 educators as part of Phase 1b announced on December 23 may, in fact, indicate an initial preference for exposure-based prioritization.[16]

Rather than being on track for adopting an age-based approach to vaccine prioritization from the beginning, Oregon *fell into* an age-based approach as a result of several factors exogenous to the treatment variable: the pace of the roll out, the expansiveness of Phase 1a, and—most importantly—the timing of the change in the CDC guidelines with respect to its planning of Phase 1b. Had the change in the CDC guidelines happened after its committee had already finalized its Phase 1b—as was the case in California—we might have seen Oregon open vaccine eligibility to grocery employees at the same time as California.

Conversely, had California been slightly behind in its prioritization at the time of the change in the CDC guidelines—for example, had some of its counties not already started contacting agriculture and food workers, per Governor Newsom's January 4 announcement—its vaccine prioritization could have looked much more like that in other states that followed

[16]Though both Oregon and California have strong teachers' unions (Winkler, Scull, and Zeehandelaar 2012), California's teachers' union had dedicated more resources in lobbying Governor Newsom for early vaccine access to educators (Morre and Rowan 2021). Yet Oregon opened vaccine eligibility to teachers more than a month before California.

an age-based approach.

### Summary of Case Study Evidence

All in all, the case study evidence strengthens the justification for the unconfoundedness assumption. While without the context, it looks like the two states formulated very different prioritization plans, at a closer look, no such clear divergence existed. In fact, the analysis of the two states' vaccine advisory committee deliberations reveals a remarkable similarity, despite an absence of coordination. Earlier in the process, for example, the vaccine advisory committees in both states discussed a combination of an age-based and an occupation-based approach. In the end, the determining factor turned out to be the timing of the change in the CDC guidelines on January 12, 2021, with respect to the progress in each state's planning. Both states reacted to this change in guidelines by shifting towards the age-based approach. At the time of the change, however, California happened to be slightly ahead of Oregon in its planning and progression through the vaccine priority list: Governor Newsom had already announced vaccine priority for several groups, including grocery employees, and several small counties had already been contacting these groups for a few days. As a result, while Oregon responded to the change in the CDC guidelines by simply moving to an age-based approach, California kept the already announced priority level for several occupation-based groups as Phase 1b, though in practice, these groups were still pushed back in line behind the newly added age-based priority group. In other words, the choice of prioritization approach were not as set in stone as it may look like in hindsight. Had the change in the CDC guidelines not taken place, we may have well seen more states, including Oregon, adopt what would have looked like an occupation-based approach.

Rather than customizing vaccine prioritization to their local political or demographic context, the two states simply did their best to adhere to the national guidelines, however vague. The evidence also suggests that the variation in state-formulated priority lists was due to stochastic, rather than systematic factors, such as variation in interpreting the CDC guidelines, a failure to anticipate the pace of increases in vaccine supply, and idiosyncratic delays in VAC decision-making.

## Appendix E. Case Studies: California and Oregon

In order to gain a better understanding of state-level decision-making in formulating vaccine priority lists, I studied the records (minutes from meetings, meeting summaries, slides, video recordings, and other materials) made available by the California and Oregon vaccine advisory committees (CVAC and OVAC, respectively),[17] as well as contemporaneous news stories and press releases. The goal of these two case studies is to trace the process that resulted in the similarities and differences in vaccine prioritization plans between the two states. Given the endogeneity concern, the main point of interest is to evaluate whether the primary drivers for these differences were systematic (e.g., political goals, state demographics) or idiosyncratic.

Rather than formulating nationwide vaccine prioritization and distribution policies, the Trump administration delegated most of these tasks to the states. Several federal agencies, including the Center for Disease Control (CDC) and the National Academy of Science, Engineering, and Medicine (NASEM) offered broad recommendations with an understanding that each state will tailor these guidelines to its own specific circumstances. Despite such seemingly wide decision-making latitude, states ended up with remarkably similar prioritization plans that largely adhered to the CDC guidelines, especially at early stages. The key differences in state-level outcomes involved the rate of progression through the phased approach (the rate at which the state opened eligibility to groups with the next level of priority), the expansiveness of the definitions for various CDC-recommended groups, and the relative place in the vaccine queue (sub-prioritization within Phase 1b) allocated to several relatively small occupation-defined groups (educators, agricultural and grocery workers, correctional facilities, etc.).

To preview the main result from the case studies, these differences were largely caused

[17] California materials are available from https://www.cdph.ca.gov/Programs/CID/DCDC/Pages/COVID-19/Community-Vaccine-Advisory-Committee.aspx, Oregon materials are available from https://www.oregon.gov/oha/ph/preventionwellness/vaccinesimmunization/immunizationpartnerships/pages/covid-19-vaccine-advisory-committee.aspx.

by a randomizing event—an abrupt change in the CDC guidelines on January 12, 2021—and each state's place in their own prioritization campaign at the time of this randomizing event. The change in the CDC guidelines was a reversal of the previous recommendation to prioritize individuals based on both health and occupational risks. Instead, as of January 12, 2021, the CDC issued a strong recommendation to use age as the primary criterion for prioritizing vaccinations and to prioritize vaccine access to individuals 65 and older. The case study demonstrates that, prior to the randomizing event, both California and Oregon were on path towards very similar prioritization lists, with perhaps minor differences in sub-prioritization. In response to the randomizing event, both California and Oregon reshuffled their sub-prioritization lists so as to move individuals 65 and older up in the vaccine line. The only difference was each state's current progress through their own prioritization stages at the time of the randomizing effect: while as of January 12, 2021, California had already started vaccinating agricultural and food workers as part of their Phase 1b Tier 1, Oregon was still finalizing their Phase 1a.

#### The Timeline of Vaccine Roll-Out in California and Oregon

**Phase 1a.** Figure 6 provides a visualization of each state's vaccine roll out timeline. Each state started Phase 1a of the vaccination campaign in the middle of December 2020, shortly after the two Covid-19 vaccines (Pfizer/BioNTech and Moderna) received emergency authorization from the CDC. The task of formulating vaccine priority lists was assigned to state health authorities—the California Department of Public Health (CDPH) and the Oregon Health Authority (OHA)—who were to work in consultation with the governor's office. In both states, these groups consisted of career medical professionals—medical doctors, professors of medicine, and heads of medical research institutes. Though the final authority rested with the governors' offices, there was only one instance, in which the governor seemingly preempted the committee's recommendations to advance a group in the priority list.[18]

[18] This exception is Oregon's Governor Kate Brown's giving higher priority to educators employed in K-12 (Ross 2020). As I explain below, this exception does not pose a threat of introducing confounding bias to the

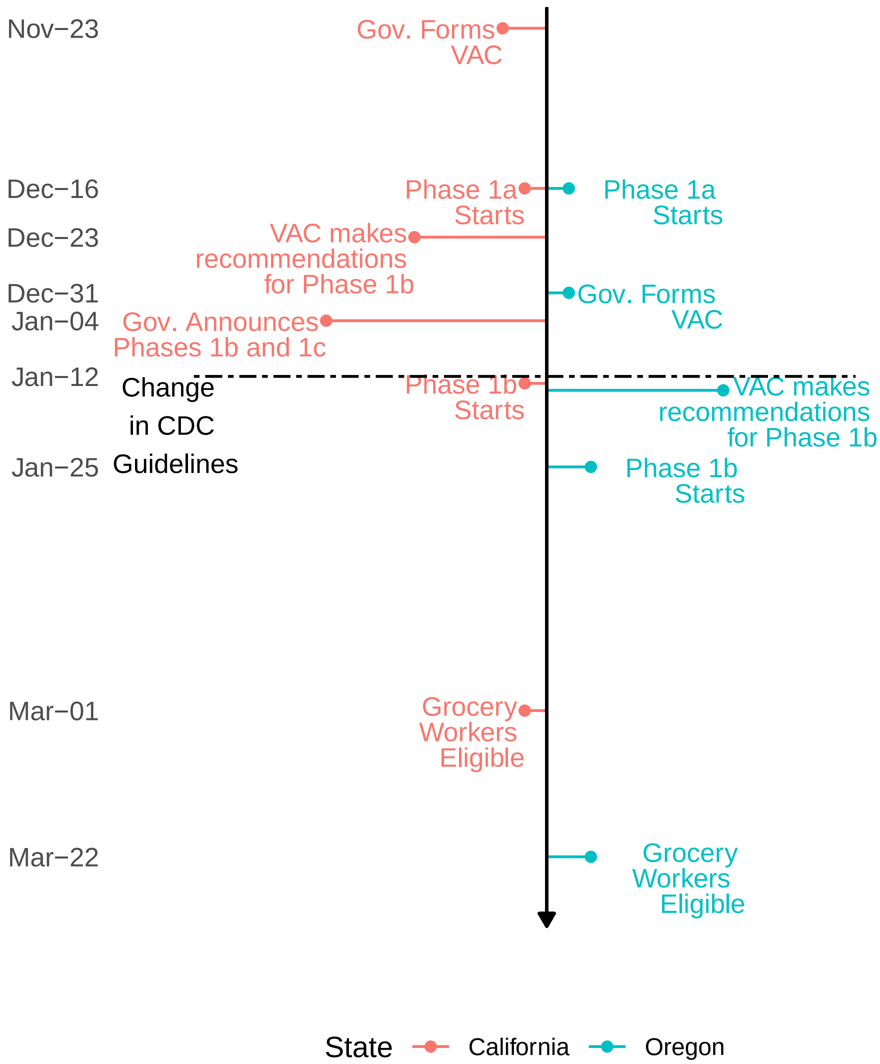


Figure 6: Decision-Making Timelines for California and Oregon. The dot–dashed horizontal line shows the Timing of the Change in the CDC Guidelines.

The starting point for prioritization within Phase 1a was each state's interpretation of the CDC guidelines to prioritize (1) healthcare workers, such as EMTs and paramedics; and (2) other essential workers, including law enforcement and fire safety (CVAC Nov. 25, 2020, 9). Both states followed the first guideline[19] and prioritize healthcare workers as part of their Phase 1a, though Oregon chose a more expansive definition. While California's definition of health workers was limited to any personnel with direct interaction with patients,

study. This exception does, however, set up conditions for a placebo test of the network theory predictions, as shown in Section *Validating Assumptions* in the article.

[19]Both California and Oregon prioritized law enforcement and fire fighters as Phase 1b.

Oregon had no such qualifications and also included any non-medical personnel of healthcare facilities, such as cleaners and food servers (OVAC, Jan. 14, 2021). In addition to healthcare workers, both states' Phase 1a included residents of long-term care facilities (CVAC Nov. 30, 6). Oregon also included several additional groups, such as individuals with developmental disabilities, employees of early learning centers, and individuals working in death care services (OVAC Jan. 14, 2021).

The practical implication of adopting a more expansive definition of essential health care personnel, and by including more groups in Phase 1a, was a slight delay in Oregon's timeline for planning of future priority lists (Phases 1b and lower) and its advancement from Phase 1a to Phase 1b. None of the additionally-included groups were very large, so the difference in the timeline was only about two weeks. California started Phase 1b on January 13, whereas Oregon's Phase 1b started on January 25. This difference in the timelines, however, happened to coincide with the randomizing event—the unexpected change in the CDC guidelines announced on January 12.

**Planning for Phase 1b—Prior to January 12, 2021.** Figure 7 shows each state's timeline for Phase 1b. While Phase 1a prioritization was done by the health authorities and the governor's office, the planning of Phase 1b and later phases included formation of an additional vaccine advisory committee (VAC) that helped represent diverse communities across each state.[20] In practice, the goals of VACs were to provide an advisory recommendation on the groups to be prioritized and sub-prioritized in Phases 1b, 1c, and 2, as well as to add transparency, equity, and accountability to the vaccine allocation process. To help accomplish these goals, VACs in both states held frequent public meetings (with video recordings, materials, and minutes available online), in which the committee watched presentations by health officials, followed by lengthy Q&A sessions, discussion and deliberation, and formulation of the recommendations to submit to the health authorities. These meetings, especially

[20] VACs were formed in response to NASEM's recommendation of setting up a framework "where public and community voice could be heard and incorporated into the process" (CVAC Feb. 3, 2021, 3; Oregon Health Authority (2020)].

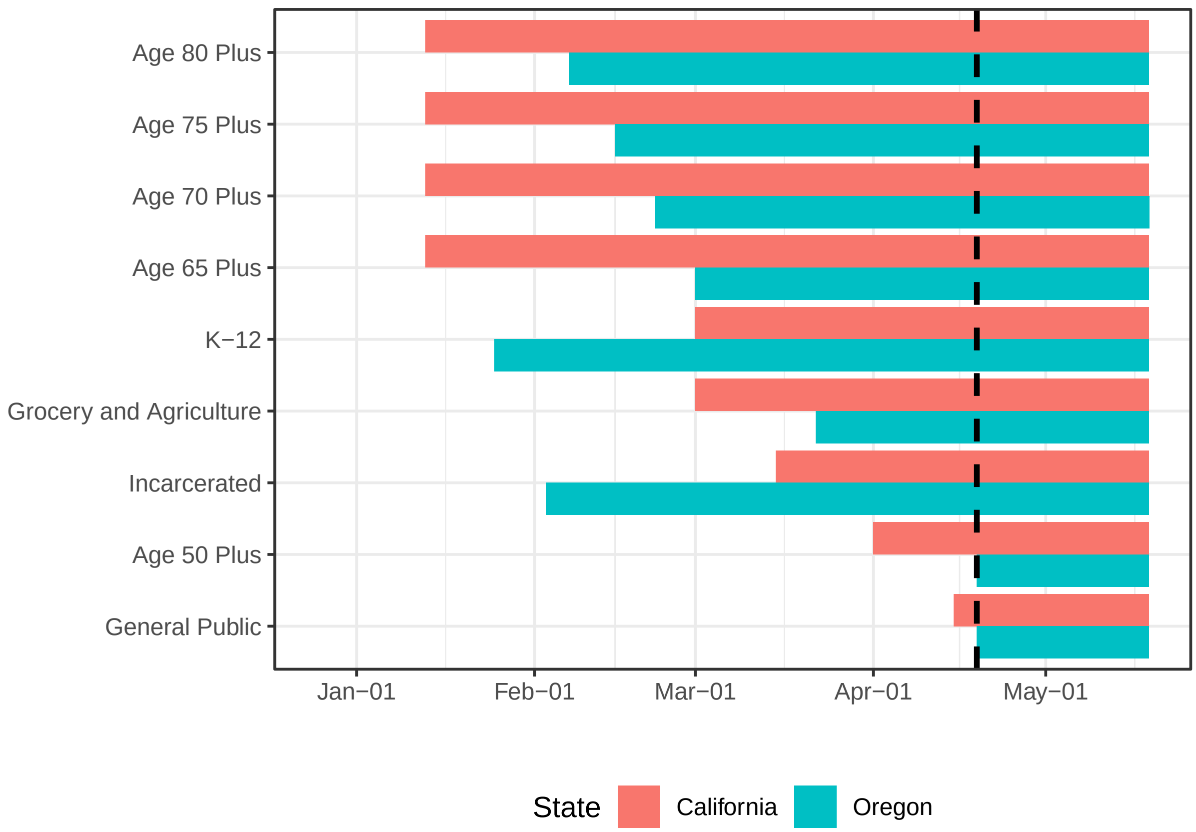


Figure 7: Prioritization Timelines for California and Oregon. The dashed vertical line shows the data of open vaccine eligibility in both states.

the Q&A with the health officials, provide a window into otherwise opaque decision-making by the CDPH, OHA, and the governors' offices in both states.

A notable difference between the two states is that California formed its VAC in late November, 2020 (California Department of Public Health (CDPH) 2020), while Oregon did not finalize the membership of its VAC until December 31, 2020 (Oregon Health Authority 2020). In terms of the vaccine rollout schedule, this meant that Oregon's VAC was formed at the tail end of Oregon's Phase 1a, which put the committee on a rather short timeline, giving it less then two weeks to review all the pertinent information and formulate a recommendation. California' VAC, in comparison, had about a month of a head start over Oregon.

In practical terms, this translated into a difference of three meetings or about 6 hours of extra discussion/deliberation time for California's VAC: prior to January 12, 2021—the timing of the randomizing event—California's committee help six meetings, whereas Oregon's committee was able to meet only three times. The significant of this difference in timing became apparent only in hindsight. Neither state coud a priori envision the January 12, 2021, change in the CDC recommendations.

The slight delay in forming a VAC in the case of Oregon is easily explained by its more expansive Phase 1a criteria that had put it on a slightly slower schedule in terms of transitioning to Phase 1b, compared to California. Given the slow progress of Phase 1a, the OHA were in no rush to form a VAC that would help determine priorities for Phases 1b, 1c, and 2. Every part of the planning, especially as it relates to anticipating the timing of progressing through the vaccine rollout phases was also complicated by the uncertainty as to the timing of possible increases in vaccine supplies—another randomizing factor. Early vaccine shipments were small and inconsistent: states had little advanced information of the number of expected doses. The combination of a complicated manufacturing process and very restrictive handling requirements (e.g., the use of ultra cold freezers) resulted in frequent shipment delays and smaller than expected deliveries. For example, a February snow storm resulted in unexpected delivery delays in California (Hajibabai et al. 2022, 8–9).

This head start allowed California to finalize and publicly announce its priority lists for Phase 1b and 1c on January 4, 2021 (Newsom 2021). Tier 1 Phase 1b—set to open on January 13, 2021—was to include individuals of age 75 or older, educators and childcare workers, emergency service employees, and individuals employed in food and agriculture (CVAC Jan. 6. 2021, 7). The last category included grocery store employees—the group of theoretical relevance for this study.

In an act with important ramifications for this study, a number of smaller counties, which had already completed vaccinating everybody who were eligible under Phase 1a, started contacting the groups announced by the governor prior to the scheduled start date of January 13, 2021.[21]

[21] California allowed individual providers limited discretion so as to avoid wasting doses (CVAC Jan 12, 2021, 12).

In contrast to California, as of January 7—its last meeting prior to January 12—Oregon's VAC was still reviewing the information and was only set to start formulating its recommendations in its next few planned meetings that were to take place on January 12 and January 17.

**Planning for Phase 1b—Post January 12** On January 12, the CDC issued a sudden revision to its prior recommendations. The new guidelines were to use age as the primary criterion for prioritizing vaccinations and to expand eligibility to individuals over age of 65 as well as people 16–65 with pre-esisting medical conditions. This new recommendation was motivated by the disproportionate numbers of hospitalizations, ICU admissions, and deaths among the individuals in these groups (CVAC Jan. 12, 2021, 3). Notably, these revised recommendations were made public with no advance notice to the states (Brown 2021).

Both states responded to this change in guidelines in the exact same way—by modifying their vaccine prioritization lists so as to include individuals aged 65 and older. Oregon's Governor Kate Brown announced the change in the CDC guidelines and her decision to include this group in the Phase 1b, in the same press conference on January 12 (Brown 2021). Such a quick reaction would have allowed little time for consultation with state health officials. This indicates a preference for adhering to the federal guidelines rather than tailoring the federal recommendations to local conditions—evidence against state self-selection into most favorable vaccine prioritization strategies.

The addition of individuals 65 and older, together with the December 23 directive to prioritize K-12 staff and educators, essentially pre-determined the composition of Oregon's Phase 1b, taking the decision-making out of the hands of Oregon's VAC. At the January 14 meeting of Oregon's VAC, the committee was informed of these changes and asked to issue a recommendation as to the prioritization of any additional groups. The committee recommended prioritizing expanding Phase 1b to include historically underserved communities of color, refugees populations, individuals with chronic conditions, individuals in custody, adults living in multi-generational homes, as well as frontline workers not already in Phase 1a or 1b (OVAC, Jan. 14, 2021). Importantly for the current study, frontline workers were defined to include agricultural workers, food processors, and other hourly workers who cannot work from home (OVAC, Jan. 21, 2021). Notably, though Oregon VAC's decision-making timeline lagged compared to California, Oregon itself was still at the tail end of Phase 1a at the time of these decisions.

Likewise, in an emergency meeting of the VAC, California's Department of Public Health (CDPH) proposed expanding the previously announced Tier 1 of Phase 1b to include individuals of ages 65 to 74, in addition to previously defined groups. This change would add 4.25 million Californians, expanding the total number of individuals eligible as part of Tier 1 of Phase 1b to about 12 million people (CVAC Jan. 12, 2021, 6).

As a result, California began "the transition from an age- and sector-based approach to an age-focused approach to vaccine prioritization" (CVAC Feb. 3, 2021, 13]. Combined with the already existing guidelines to sub-prioritize based on individual-specific factors, such as age, this transition effectively placed individuals aged 65 and older ahead of the rest of previously prioritized groups in Tier 1 of Phase 1b, such as childcare providers, educators, first responders, and employees of the agriculture and food sectors.

The decision to *expand* Tier 1 of Phase 1b, rather than to scrap the previously defined occupation-based prioritization altogether, stemmed from an equity consideration, as some smaller counties had already begun contacting individuals who had qualified as part of Tier 1 of Phase 1b prior to the change in guidelines (CVAC Feb. 3, 2021, 19). Once the new guidelines were announced, occupation-based prioritization was effectively suspended until the state was able to vaccinate the bulk of individuals aged 65 and older.[22]

[22]The framing of this change as an *expansion* of Tier 1 of Phase 1b, when in actuality individuals aged 65 and older were effectively placed ahead of other groups within this tier, caused some confusion. In the February 3 meeting of CVAC, several members pointed out that the state online appointment system no longer allowed childcare, food and agriculture workers to sign up for vaccine appointments, despite the continued assurances from the CDPH that they were still a part of Tier 1 of Phase 1b (CVAC Feb 3, 2021, 16).

**The January 12 Change in the CDC Guidelines as the Randomizing Event** The above description shows that the change in the CDC guidelines was an unexpected shock to the two states' prioritization processes. Prior to this change, California's health officials argued that whereas the data showed greater risks for individuals aged 75 and older, those aged 65-74 had a significantly lower risk and could be given a lower priority (CVAC Dec. 23, 2020, 10). In fact, California's committee recommendations formulated prior to the change in guidelines placed people aged 65 and older in Tier 2 of Phase 1b, behind individuals employed in education and childcare, emergency services, and food and agriculture (CVAC Jan. 6, 2020, 7).

While at the time of the change, Oregon was about two weeks behind California in the planning process, occupation-based prioritization was also a large part of the discussion in Oregon's committee. In the January 7 meeting, the OHA listed essential workers as the first out of three groups to be discussed as candidates for Phase 1b prioritization (along with individuals with high-risk medical conditions and individuals 65 and over) (OVAC, Jan. 7, 2021). While Oregon's committee did not reach the stage of making recommendations until after January 12, the information shared by the OHA in the pre-January 12 meetings, and the discussions that ensued, give no indication that Oregon's committee was set on age-based prioritization prior to January 12. Oregon Governor's decision to prioritize K-12 educators as part of Phase 1b announced on December 23 may, in fact, indicate an initial preference for occupation-based prioritization.

Rather than being on track for adopting an age-based approach to vaccine prioritization from the beginning, Oregon *fell into* an age-based approach as a result of several factors exogenous to the treatment variable: the pace of the roll out, the expansiveness of Phase 1a, and—most importantly—the timing of the change in the CDC guidelines with respect to Oregon's planning of Phase 1b. Had the change in the CDC guidelines happened after Oregon's already finalized its Phase 1b—as was the case in California—we might have seen Oregon open vaccine eligibility to grocery employees at the same time as California.

Conversely, had California been slightly behind in its prioritization at the time of the change in the CDC guidelines—for example, had some of its counties not already started vaccinating agriculture and food workers per Governor Newsom's January 4 announcement—its vaccine prioritization could have looked much more like that in other states that followed an age-based approach.

All in all, the two case studies provide strong evidence that California and Oregon (and likely other states) selection of vaccine prioritization approach followed an idiosyncratic, rather than a systematic, process. Rather than customizing vaccine prioritization to their local political or demographic context, the two states simply did their best to adhere to the national guidelines, however vague.

Political motives are ruled out based on the analysis of the political participation of the groups, whose place in the eligibility queue differed between the two states: K-12 educators and staff, the incarcerated individuals, grocery workers, and the elderly. Two of these four groups—the incarcerated individuals and grocery workers—are low-probability voters. Though both Oregon and California have strong teachers' unions, California's teachers' union had dedicated more resources in lobbying Governor Newsom for early vaccine access to educators (Morre and Rowan 2021). Yet Oregon opened vaccine eligibility to teachers more than a month before California. Teachers, moreover, make up a relatively small proportion of the likely voters in both states: Oregon's 105,000 teachers make up less than 3 percent of the population, and California's 319,004 teachers make up less than 1 percent of the population.[23] Lastly, the elderly were in the top tier of Phase 1b in both states, though with slightly later eligibility dates in Oregon—a difference due to the slower overall pace and a more expansive definition of Phase 1a.

A lack of a clear political strategy suggests that state governors treated the task of prioritization more as an opportunity to prove their competency to solve a crisis than as a yet another resource to divvy in exchange for political support. This is consistent with

[23]Oregon's numbers are based on Botkin (2021), California's numbers are obtained from California Department of Education (2019).

the findings in the literature on national disasters (Gasper and Reeves 2011; Quiroz Flores and Smith 2013; Ashworth, Bueno de Mesquita, and Friedenberg 2018). High degree of conformity between the state-formulated plans and the CDC guidelines[24] reinforce this explanation: adhering to the federal guidelines sets up an opportunity to shift the locus of accountability should things go awry—a reasonable precaution, given the high degree of informational uncertainty at the time of decision-making.

Evidence also points against demographics-based self-selection. Strict adherence to the federal guidelines, emulation of plans adopted by nearby states,[25] and high conformity in state-formulated plans indicates that the states were unwilling to exercise the freedom to tailor prioritization to the local conditions. The bottom line is that the states simply lacked information,[26] or in certain cases, even the legal authority[27] to effectively customize prioritization to the state demographic characteristics.

Instead, the case study evidence shows that any variation in state-formulated priority lists was due to stochastic rather than systematic factors, such as variation in interpreting the CDC guidelines, a failure to anticipate the pace of increases in vaccine supply, idiosyncratic delays in VAC decision-making.

[24]Both states health authorities emphasized the need to adhere to the national guidelines throughout VAC deliberations. California health officials, for example, have explicitly stated that CVAC "plan[s] to start from the NASEM framework and national recommendations" and that they "would want a strong rationale for California to deviate from these guidelines" (CVAC Nov. 25, 2020, 5). Oregon's health authorities made similar statements.

[25]Oregon's VAC, for example, had discussed Washington's prioritization approach prior to formulating its own (OVAC, Jan. 14, 2021).

[26]At the time of prioritizing groups for Phases 1a and 1b, the data as to vaccine efficacy at preventing milder disease, death, or transmission were still pending (DGW, Jan. 12, 2021, 1]. The first mention of vaccine's effectiveness at decreasing transmission, for example, was the March 17, 2021 meeting of the California' VAC, in the context of data collected from the clinical trials of the Johnson & Johnson vaccine that had just completed (CVAC Mar. 17, 2021, 5–6).

[27]For example, Oregon VAC initial recommendation to prioritize BIPOC populations, due to the disproportionate effects of Covid-19 on racial and ethnic minority communities, was found to violate a legal principle that race and ethnicity not be a sole determinant of service and resources allocation (OVAC, Jan. 21, 2021).

## Appendix F. Robustness Checks

I estimate the model on two additional outcome variables: Covid-related hospitalization and deaths, as well as an alternative specification, in which I replace control variables with county fixed effects.

For hospitalizations, I expect the effect to become apparent about four weeks after the onset of the treatment: it takes about two weeks to develop symptoms upon contracting the virus and two more weeks to get hospitalized.[28] The results, presented in Table 5, are consistent with the main model: the difference-in-difference coefficient is negative and statistically significant. The coefficient of 0.05 indicates that the treatment is associated with an average of 5 percent decrease in hospitalizations. This estimate is likely conservative, due to the large variation in the time between the infection and hospitalization among patients. Figure 8 displays the plot of the marginal effect over time. The marginal effect starts out positive but decreasing, then flips to negative as time advances, reaching about 45 percent decrease $((\exp(-.6) - 1) \times 100\%)$ in cases 20 days after the start of the treatment period (about 31 percent decrease in the matched sample).

For deaths, I assume that the effect will become apparent roughly six weeks after the onset of the treatment: it takes about four weeks after contracting the virus to get hospitalized, and two more weeks until the patient dies of Covid-19. The results, presented in Table 6, are consistent with the main model: the difference-in-difference coefficient is negative and statistically significant. The coefficient of 0.01 (0.004 in the matched sample) indicates that the treatment is associated with an average of 1 (0.4 in the matched sample) percent decrease in deaths. This estimate is also likely conservative, due to the large variation in the time between the infection and death among patients. Figure 9 displays the plot of the marginal effect over time. The effect grows (in absolute magnitude) over time, reaching an about 6.5 percent decrease $((\exp(-0.067) - 1) \times 100\%)$ in cases in the full sample (about an 10 percent decrease in the matched sample) after 20 days.

[28] The results are robust to varying these timelines.

Table 5: The Effect of Vaccine Eligibility to Grocery Employees on Covid-19 Hospitalizations (logged)

| | Full Sample | Matched Sample |
|---|---|---|
| Day of Treatment | $0.004^{**}$ (0.001) | $0.008^{***}$(0.002) |
| California | $0.484^{***}$(0.022) | $0.555^{***}$(0.036) |
| California$*$Day of Treatment | $-0.054^{***}$(0.002) | $-0.046^{***}$(0.003) |
| Cumulative Hospitalizations, logged | $0.497^{***}$(0.007) | $0.389^{***}$(0.015) |
| County GDP, logged | $0.150^{***}$(0.021) | $-0.012$ (0.083) |
| County Population, logged | $0.571^{***}$(0.019) | $-0.031$ (0.106) |
| Unemployment Rate | $-0.040^{***}$(0.002) | $-0.037^{***}$(0.011) |
| Percent BA Degree | $0.006^{*}$ (0.003) | $0.086^{***}$(0.005) |
| Urbanization | $0.004^{***}$(0.001) | $0.014^{***}$(0.001) |
| Percent Black | $0.070^{***}$(0.003) | $-0.033$ (0.036) |
| Percent Latino | $0.016^{***}$(0.001) | $0.044^{***}$(0.005) |
| Percent Other Race | $0.023^{***}$(0.001) | $0.057^{***}$(0.005) |
| Percent Foreign | $-0.012^{***}$(0.002) | $-0.038^{***}$(0.011) |
| Biden's Margin | $-0.011^{***}$(0.001) | $-0.008^{***}$(0.002) |
| Prop. Aged 65+ | $7.042^{***}$(0.237) | $3.320^{*}$(1.692) |
| Indoor Dining Ban | $0.641^{***}$(0.022) | $-0.346^{***}$(0.069) |
| New Cases/1000 res., 14-day lag | $0.097^{***}$(0.004) | $0.087^{***}$(0.006) |
| Constant | $-7.339^{***}$(0.173) | 0.366 (0.423) |
| Num.Obs. | 12220 | 2990 |
| $R^2$ Adj. | 0.91 | 0.88 |

$^{***}p < .0.05$ (two-tailed), $^{*}p < 0.1$ (two-tailed).

An alternative way to account for the cross-sectional variation is to simply replace all county-level time-invariant variables with county-level fixed effects. The trade-off is that, though the difference-in-difference design works well with either time-invariant control variables or fixed effects, proper implementation of the coarsened exact matching requires matching on covariates (one cannot match on fixed effects), as well as including these covariates in the subsequent regression specification.[29]

Nonetheless, I have also re-estimated the main model with fixed effects rather than time-invariant controls. The results are presented in Table 7. The main treatment effect—early vaccine eligibility for grocery workers—is robust to this specification.

[29] One must control for the covariates, despite using coarsened exact matching, since this matching approach matched on observables using ranges in values rather than exact values (Iacus, King, and Porro 2012).

Table 6: The Effect of Vaccine Eligibility to Grocery Employees on Covid-19 Deaths (logged)

| | Full Sample | Matched Sample |
|---|---|---|
| Day of Treatment | $-0.002^{***}(0.001)$ | $-0.003^{***}(0.001)$ |
| California | $0.198^{***}(0.014)$ | $-0.027\ (0.022)$ |
| California∗Day of Treatment | $-0.013^{***}(0.001)$ | $-0.004^{***}(0.001)$ |
| Cumulative Deaths, logged | $0.181^{***}(0.007)$ | $0.020\ (0.012)$ |
| County GDP, logged | $0.123^{***}(0.014)$ | $-0.077\ (0.049)$ |
| County Population, logged | $0.280^{***}(0.013)$ | $0.179^{**}\ (0.062)$ |
| Unemployment Rate | $-0.009^{***}(0.001)$ | $-0.019^{**}\ (0.006)$ |
| Percent BA Degree | $0.018^{***}(0.002)$ | $0.010^{***}(0.003)$ |
| Urbanization | $-0.002^{***}(0.001)$ | $0.002^{***}(0.001)$ |
| Percent Black | $0.043^{***}(0.002)$ | $0.111^{***}(0.021)$ |
| Percent Latino | $0.009^{***}(0.001)$ | $0.015^{***}(0.003)$ |
| Percent Other Race | $0.013^{***}(0.001)$ | $-0.008^{**}\ (0.003)$ |
| Percent Foreign | $-0.002^{\dagger}\ (0.001)$ | $0.008\ (0.006)$ |
| Biden's Margin | $-0.008^{***}(0.001)$ | $-0.005^{***}(0.001)$ |
| Prop. Aged 65+ | $3.657^{***}(0.160)$ | $3.922^{***}(0.919)$ |
| Indoor Dining Ban | $0.423^{***}(0.015)$ | $-0.031\ (0.036)$ |
| New Cases/1000 res., 28-day lag | $0.017^{***}(0.003)$ | $0.026^{***}(0.003)$ |
| Constant | $-5.522^{***}(0.108)$ | $-1.092^{***}(0.233)$ |
| Num.Obs. | 15604 | 3818 |
| $R^2$ Adj. | 0.69 | 0.43 |

$^{***}p < .0.05$ (two-tailed), $^{*}p < 0.1$ (two-tailed).

Table 7: The Effect of Vaccine Eligibility to Grocery Employees on New Daily Covid-19 Cases (logged)

| | Full Sample | Matched Sample |
|---|---|---|
| Constant | $4.455^{***}(0.094)$ | $2.973^{***}(0.051)$ |
| Day of Treatment | $-0.006^{***}(0.001)$ | $-0.010^{***}(0.002)$ |
| California | $1.803^{***}(0.077)$ | $-0.383^{***}(0.071)$ |
| California∗Day of Treatment | $-0.037^{***}(0.002)$ | $-0.029^{***}(0.003)$ |
| New Cases/1000 res., 3-day lag | $0.275^{***}(0.004)$ | $0.151^{***}(0.006)$ |
| County Fixed Effect | yes | yes |
| Num.Obs. | 10904 | 2668 |
| $R^2$ Adj. | 0.91 | 0.88 |

$^{***}p < .0.05$ (two-tailed), $^{*}p < 0.1$ (two-tailed).

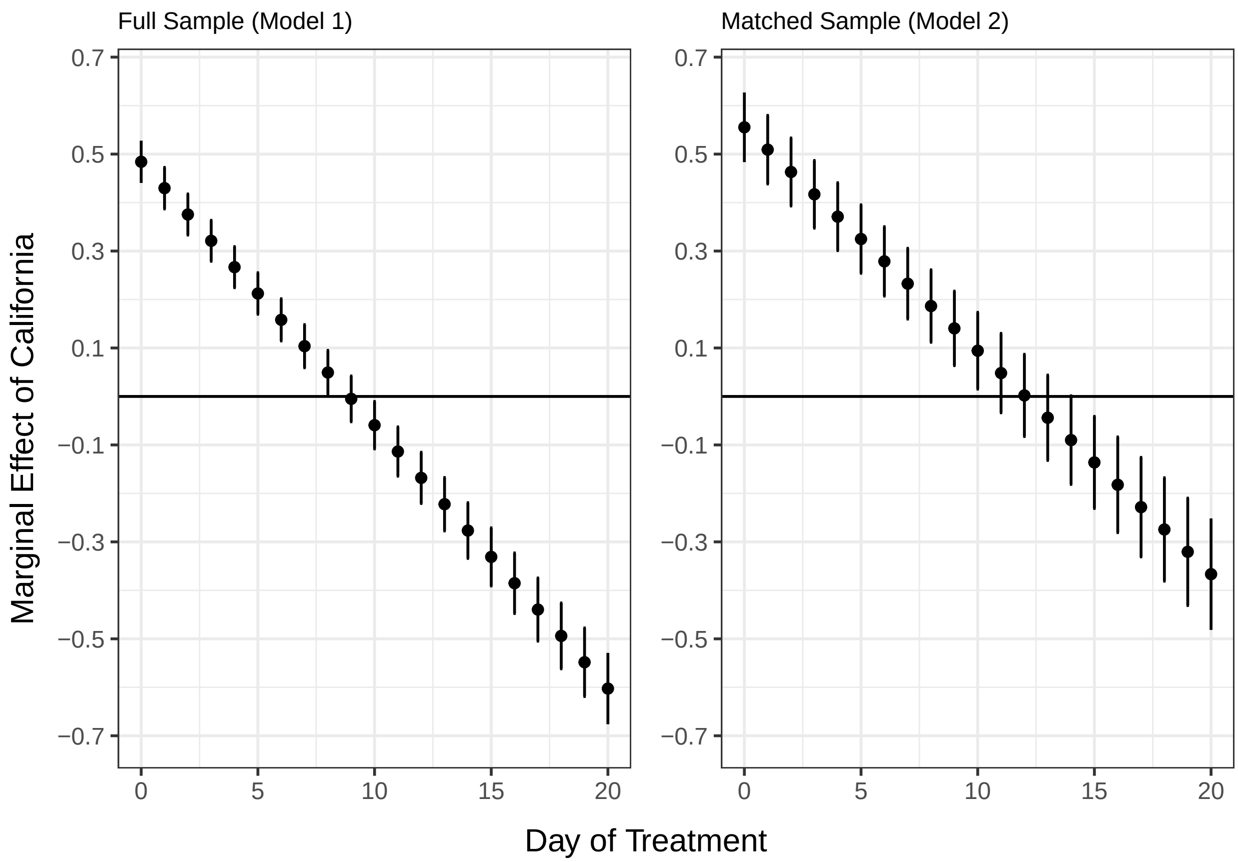


Figure 8: Marginal Effect of Vaccine Eligibility to Grocery Workers On Hospitalizations. Error bars represent 95% CIs.

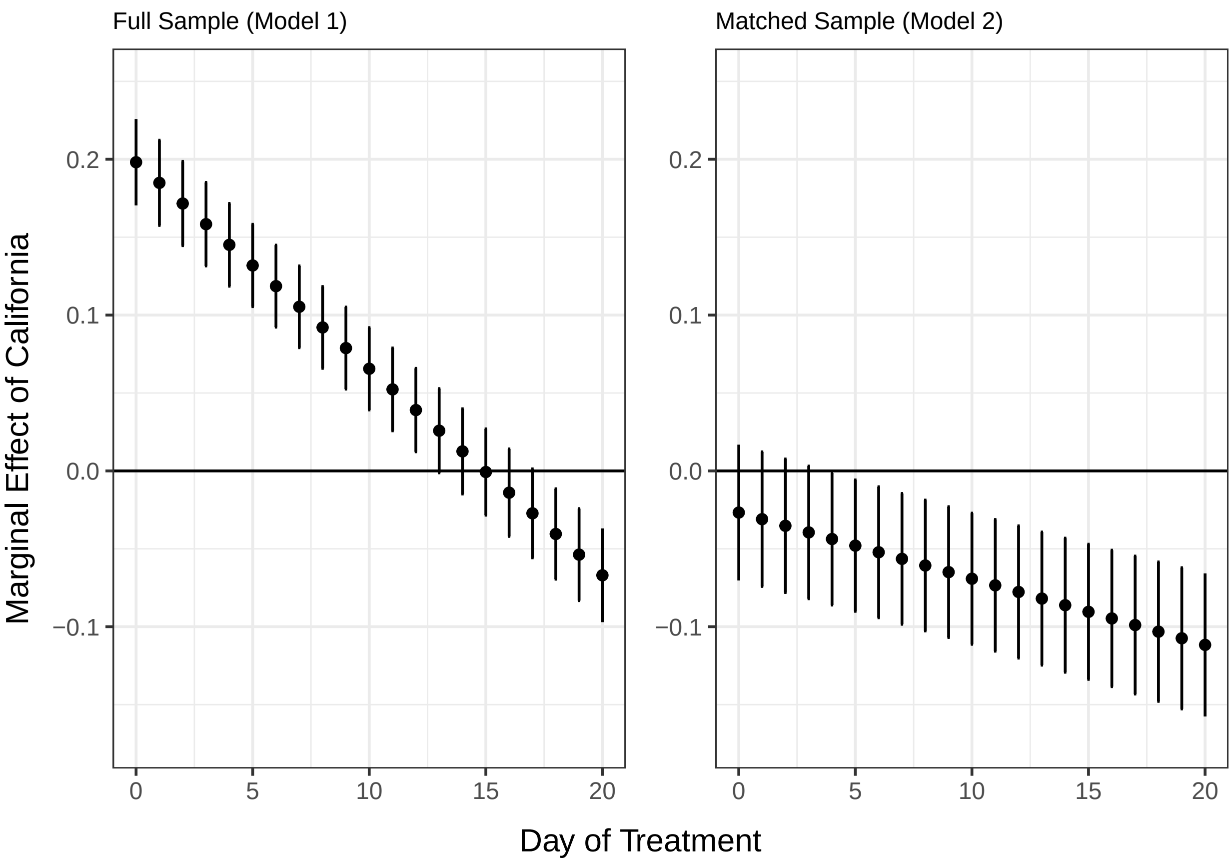


Figure 9: Marginal Effect of Vaccine Eligibility to Grocery Workers On Covid-19 Deaths. Error bars represent 95% CIs.

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