Title: Prison Connectivity and Disease Transmission in Neighboring Communities

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Abstract: While it has been recognized that "closed institutions" like prisons pose health risks to residents, the degree to which these risks spread to surrounding communities is not well understood. Analyzing smartphone movements, we document geographic variation in how connected California communities are to neighboring prisons and find that these linkages spread infectious diseases. We study a prisoner-transfer-induced San Quentin COVID-19 outbreak in June of 2020 as a quasi-experiment, and document that zip codes connected through prison-worker contact had 13% more new cases in July and 30% more in August compared to epidemiologically and demographically-matched controls. This suggests that "closed institutions" are—even during lockdowns—epidemiologically porous, highlighting the need for public health interventions to reduce the unintended consequences of such connections on the spread of infectious disease.

One-Sentence Summary: We study how prisons spread infectious diseases to neighboring communities, using a prisoner-transfer COVID-19 outbreak as a quasi-experiment.

Main Text:

In 2011 Plata v Brown, the U.S. Supreme Court confirmed what many scholars and advocates had long argued—that the American incarceration system creates a substantial public health burden. People who interact with the criminal legal system have worse health outcomes along almost every dimension (*1*), but two recent revolutions in technology and global health—the rise of GIS-enabled smartphones and the COVID-19 pandemic—allow us to shed new light on one specific way that prisons can impact community health, identifying a previously underrecognized channel—prison officers and staff—through which incarceration can be a vector to transmit upper respiratory diseases to communities.

The largest COVID-19 outbreaks have occurred in "closed institutions," such as prisons, jails, and nursing homes (*2,3*). These facilities concentrate various vulnerabilities—e.g., confined physical spaces and overcrowding, limited resources and personal protective equipment, and individuals with socioeconomic disadvantages and health comorbidities—into places of extreme risk. Indeed, U.S. prisons were sites of 39 of the country's 50 largest COVID-19 outbreaks in 2020 (*3*). People incarcerated in prisons, compared to the general population, were five times as likely to experience COVID-19 infection and three times as likely to die from COVID-19 (*4*).

The ramifications for disease transmission from prison COVID-19 outbreaks to the general population is unknown. On the one hand, prisons may pose little risk to the general population. Beginning in March 2020, prisons across the country locked down their facilities, prohibiting visitors and programming. Although state agencies made different decisions regarding when to reopen (*5*), they appear to have responded to general population case rates, closing back down when infections were rising in facilities and communities. On the other hand, despite these lockdowns, prisons are actually more porous than many realize, with staff continually moving back and forth between their homes and workplaces (*6*). Notably, in most jurisdictions, agencies did not implement universal staff testing for COVID-19 (*7*), and mask mandates were not consistently enforced (*8*). Consequently, large prison outbreaks may have facilitated disease transmission to the general population.

To date, there is no assessment of prisons as population-level risk factors for disease transmission, including COVID-19 transmission. However, related studies focusing on jails (which usually include a shorter confinement period than prisons)—and the cycling of people between jails and their homes—indicate that carceral facilities have harmful ramifications for their surrounding communities (*9,10*). In an article focusing on releases from Cook County jail in March 2020, releases are estimated to account for 13% of all COVID-19 cases in Chicago by August 2020 (*10*). This research provides an important accounting of disease transmission, but observational studies are limited by endogeneity issues, with staff and officers as one example of potential sources of unobserved heterogeneity.

We leverage multiple sources of "big data," specifically smartphone location data purchased from Veraset and publicly-available prison property boundary line data from the Department of Homeland Security to provide novel evidence on how connected different California communities are to prisons and how those connections are related to disease transmission from prisons to communities. These data include high-quality and fine-grained information on which individuals travel to and from prisons and how long they spend in prisons and non-prison locations. We also replicate these analyses with publicly-available LODES (LEHD Origin-Destination Employment Statistics) data from the Census Bureau, which contain limited information on the communities where prison staff live, to illustrate how researchers can effectively model prison connectivity and disease transmission in neighboring communities in future research.

The smartphone GPS data have been previously used to document the mobility of nursing home employees (*11*), police officers (*12*), and tech firm employees (*13*). The data include "pings" indicating the location of a smartphone at a particular point in time. Pings are logged whenever a participating smartphone application requests location information, with the modal time between a phone's two consecutive pings being roughly 10 minutes. To identify people who spend time in prison, we identify phones that spend time in proximity to prison boundaries (typically within the bounds of a parking lot) at least 10 minutes a day. We then measure the connectivity between the prison and ZIP code tabulation areas (ZCTAs)—mailing areas covered by ZIP codes created by the Census Bureau and referred to as "zip codes" hereafter—by associating the total time spent in prisons for all cell phones that "live" in a certain zip code. We define the "home" of a cell phone as the zip code that the phone spends the most time when outside of prisons (in June to October 2020).

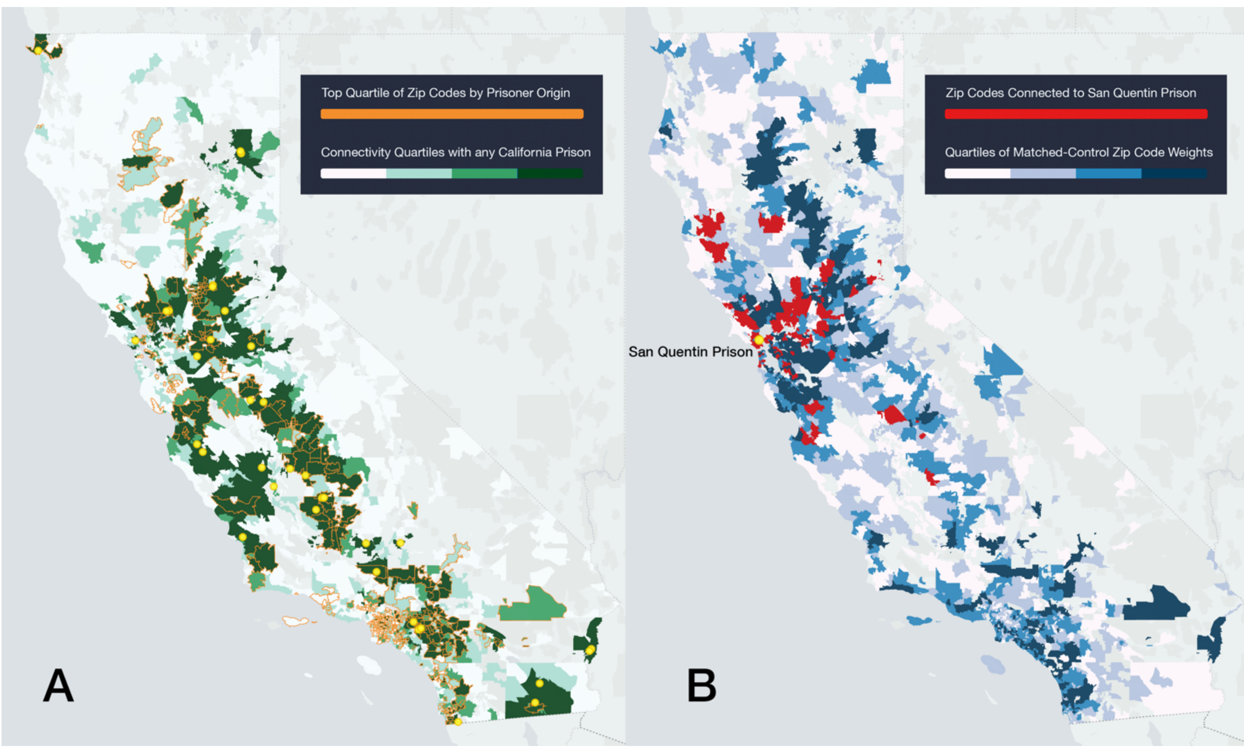


Fig. 1. Zip code connectivity to California state prisons in June 2020.

Panel (A) displays overall connectivity (quartiles in green) to all 35 state prisons in June 2020 and the top quartile of prisoner origin (outlined in orange). Panel (B) highlights zip codes connected (red) or not connected (blue) to San Quentin state prison in June 2020, with darker blue indicating higher regression-weighting for unconnected zip codes as matched-controls in our analysis.

Our smartphone data show, for the first time, which zip codes in California were the most connected to prisons in June 2020 (Figure 1a). Though not conclusive, it is likely that prison staff, rather than visitors to prisons, drive these community connections for three reasons. First, as a COVID-19 mitigation policy, California prisons prohibited in-person visitors during this time. Second, zip codes connected to a specific prison are generally close to that specific prison; for example, zip codes connected to San Quentin are generally neighboring areas close to San Quentin (Figure 1b); prison staff are more likely to live close to their place of employment than visitors are to live close to their incarcerated family member or friend. Third, the zip codes that our smartphone-based measurement identifies as connected to prisons does not necessarily correspond with the zip codes where most prisoners lived prior to incarceration (Figure 1c; also see *14*). For example, Figures 1a reveals that though the greater Los Angeles area, the most heavily populated region of California, is the largest contributor to the California prison population, it is only loosely connected to prisons on a day-to-day basis during the early pandemic identified by our smartphone-based approach.

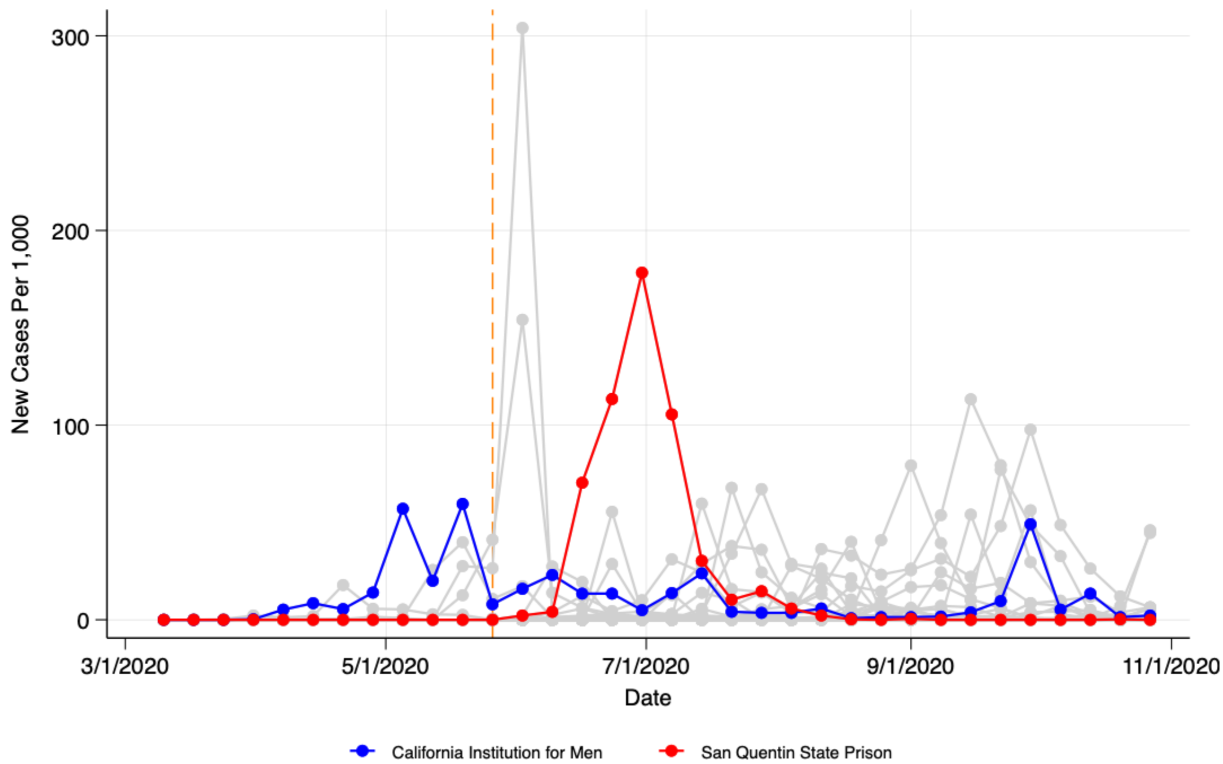


Fig. 2. Weekly COVID-19 cases per 1,000 in California state prisons.

The blue line plots new COVID-19 cases per 1,000 for California Institution for Men, the red line plots new COVID-19 cases per 1,000 for San Quentin state prison, and the gray lines plots new COVID-19 cases per 1,000 for other state prisons.

In this article, we leverage the fact that the source of one prominent COVID-19 outbreak in San Quentin state prison, in Northern California, was exogenous to that facility, caused by transferring 122 incarcerated people from the California Institution for Men, in Southern California, while the latter facility was experiencing an outbreak (*15*). Transferred prisoners tested negative for COVID-19 more than two weeks before being transferred, were placed on overcrowded buses for their transport, and 15 of those transferred tested positive for COVID-19 shortly after arriving to San Quentin. Prison administrators housed the remaining transfers in a housing unit without solid doors and allowed staff to work in multiple areas throughout the prison, all of which contributed to a massive outbreak at that facility (Figure 2). In contrast, Corcoran state prison received 67 incarcerated people from California Institution for Men and experienced a more limited outbreak. Corcoran is a newer prison compared to San Quentin, with many cells having solid doors believed to limit the spread of respiratory infection among incarcerated people (*15*). Using monthly counts of zip code-level new COVID-19 cases from the California Department of Public Health (CDPH), we can quantify the importance of prison connectivity in disease transmission to neighboring communities by testing whether this specific prison outbreak at San Quentin led to a differential increase in COVID-19 risk in the specific zip codes most connected to San Quentin prison.

We begin by dividing zip codes into one of two groups: zip codes where our smartphone data suggest a connection to San Quentin and zip codes where we do not observe a connection. Following Callaway and Li (*16*), we estimate the average treatment effect associated with being connected to San Quentin using an identification strategy that conditions on the pre-transfer zip code level COVID-19 case rates (obtained from the CDPH) and demographic variables. As (*16*) suggests, since the spread of COVID-19 cases is highly nonlinear, identification strategies that compare location with similar pre-treatment "states" of the COVID-19 pandemic are more suited to examine the impact of policies on COVID-19 transmission than difference-in-difference approaches. Specifically, this strategy involves estimating the propensity score of being connected to San Quentin, and an outcome regression for COVID-19 cases in non-connected zip codes, using demographics from the 2015-2019 American Community Survey (ACS) aggregated to the zip code level and pre-transfer COVID-19 case rates. This strategy provides a doubly robust estimate, in the sense that the estimate is consistent if either the propensity score or outcome regression is correctly specified.

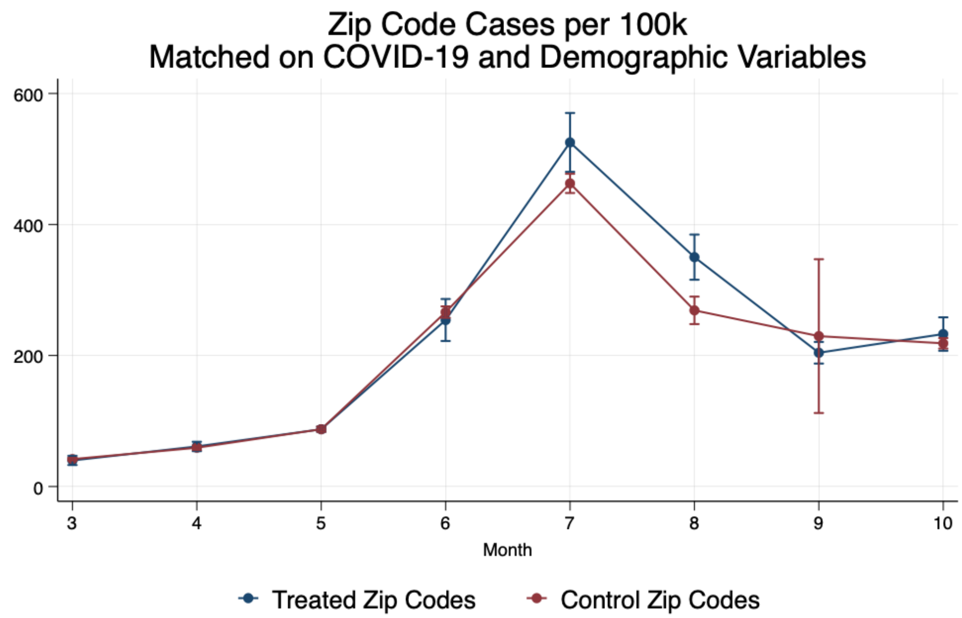
Results:

The data suggest that, one month after prisoners were transferred to San Quentin, connected zip codes experienced 62 (SE =23.9) additional COVID-19 cases per 100,000 people, and two months later this increased to 81 (SE =20.6) additional cases, before the rate of new diagnoses converged to the rate in non-connected zip codes. To put these numbers in perspective, when added to the actual rate of new COVID-19 infections in unconnected zip codes, our estimated average treatment effects show that connected zip codes had 13% more new cases in July 2020 and 30% more new cases in August 2020 (Figure 3a). Replicating these analyses using publicly-available LODES data on communities where prison staff live provides similar results, corresponding to 23% more new cases in connected zip codes in July 2020 and 37% more new cases in August 2020 (Figure 3b).

Of course, this increased rate of disease transmission could reflect the progression of COVID-19 in zip codes that were connected to prisons generally, rather than San Quentin specifically. This could be the case if zip codes that were demographically similar to zip codes connected to San Quentin, but not close to any prison, also had some other characteristic not reflected in census data that drove COVID-19 infections in mid-2020. Examples of this could include ability to comply with shelter-in-place orders (*17*), propensity to adopt personal protective equipment (*18,19*), or political affiliation (*20*).

We can explore the role of potential unobserved confounding variables by permuting our measure of connectivity across zip codes and re-estimating our average treatment effect. The distribution of possible effect sizes suggests that the observed timing of COVID-19 transmission is unique to communities connected to San Quentin, rather than communities connected to any other California prison. A total of 34 out of 1000 estimates for August generated from this permutation test were larger than 81, and 118 out of 1000 estimates were larger than 51 (Figure 4).

Panel A



Panel B

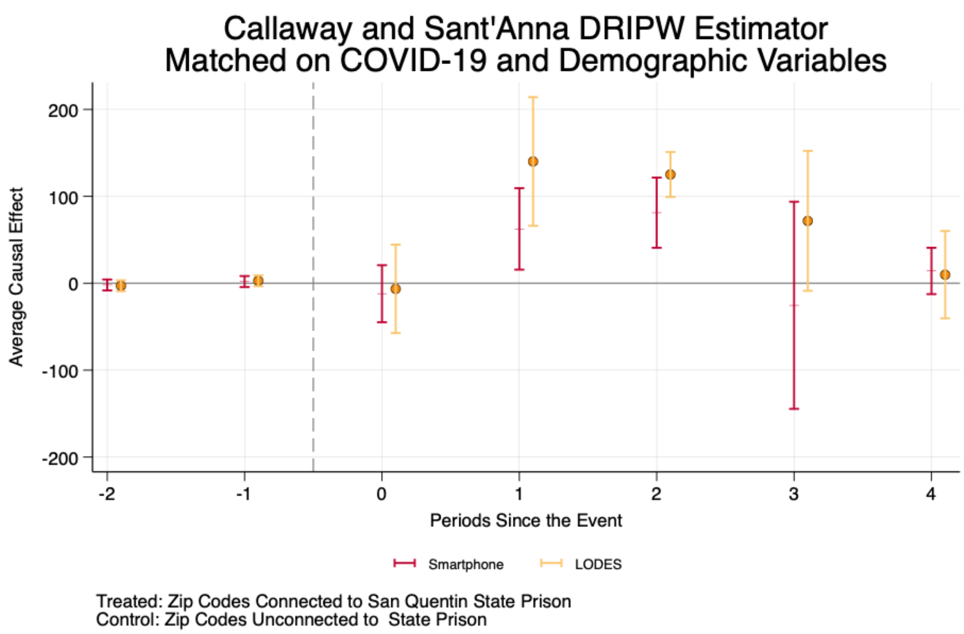
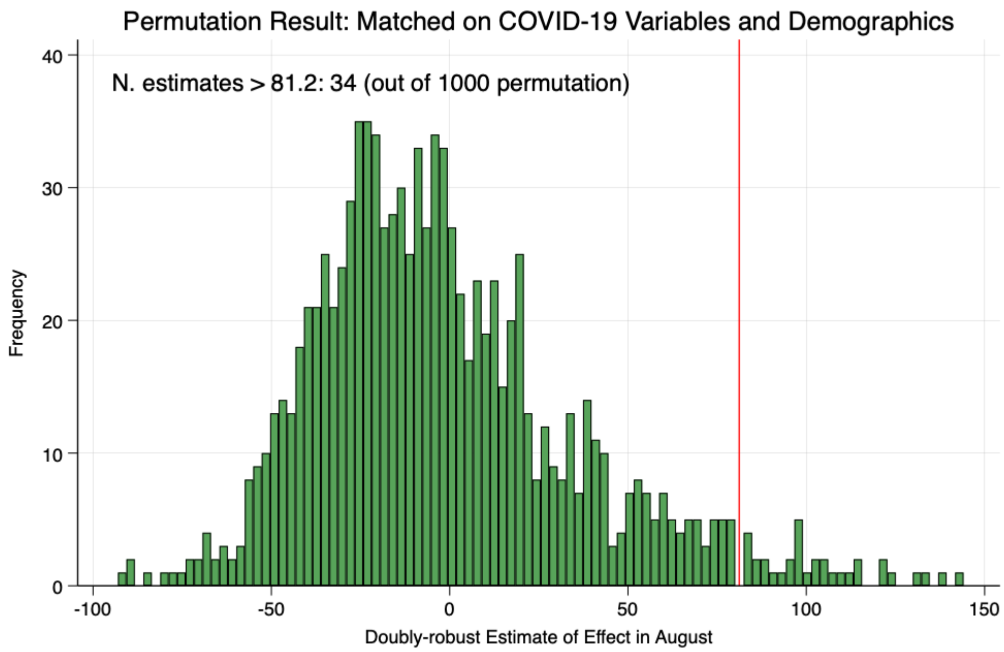


Fig. 3. Monthly COVID-19 case rate and ATE of connecting to San Quentin state prison.

Panel (a) shows the average monthly COVID-19 cases per 100,000 residents for connected and unconnected zip codes defined using the smartphone location data, with COVID-19 case rates weighted by the matching-adjustment weights for unconnected zip codes. Panel (b) presents the Average Treatment Effect (ATE) of connecting to San Quentin state prison in each month, both estimated using the smartphone location data and using the LODES data.

Panel A



Panel B

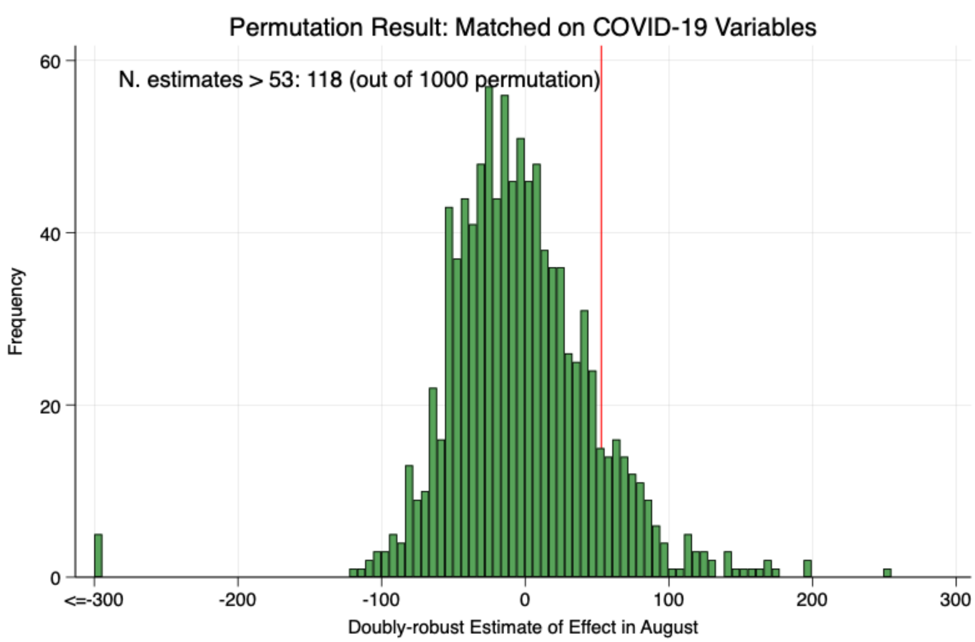


Fig. 4. Average treatment effect distributions for San Quentin state prison connectivity permutation, August 2020.

Panel (a) displays doubly robust estimates matched on COVID-19 and demographics variables when permutating the connection between zip codes and San Quentin state prison, while panel (b) plots the same doubly robust estimates matched only on COVID-19 variables.

Additional robustness tests—where we exclude outlier zip codes, vary how we define the treated zip codes, include interactions between COVID-19 and socioeconomic variables for matching, and examine zip codes connected to Corcoran prison (which experienced a more limited outbreak resulting from a transfer from the California Institution for Men)—are included in the appendix. None of these alternate specifications substantively change our findings, suggesting that the data, rather than any modeling assumptions, are driving our estimates. The fact that we identify a similar relationship in Corcoran prison is notable because COVID-19 mitigation strategies—specifically, the ability to house transferred prisoners in cells with solid doors—were considered more effective in Corcoran than in San Quentin (*8*). Indeed, the extensiveness of the San Quentin outbreak has been partly attributed to its older infrastructure, which prevented prison officials from being able to physically contain the airborne virus by keeping exposed prisoners in isolated cells, as was done in Corcoran (*8*). Other policy lapses and violations—including long lag times for testing transferred prisoners, overcrowded buses, lack of universal staff testing, and lax enforcement of mask wearing—also contributed to the San Quentin outbreak, and likely transmission outside of Corcoran as well. The California Office of the Inspector General concluded that these policy and implementation failures caused a "public health disaster at San Quentin state prison"; in this study, we identify how these failures also endangered the public health of surrounding communities, not simple the community in San Quentin.

Discussion:

While the COVID-19 pandemic may be historically unique, the underlying epidemiology is not; like all upper respiratory infections, it is easily transmitted across individuals who come into close contact with one another and the period of infectious transmission frequently precedes the appearance of symptoms. In this paper, we document geographic variation in how connected California communities are to prison environments and show evidence that these connections are relevant to the spread of infectious diseases. We use high-quality, directly observed geographic movements of prison staff to and from their communities, while also illustrating how publicly-available data from the Census Bureau can be employed to identify similar patterns of disease transmission.

Our analysis shows that disease outbreaks in prison have first order impacts on the communities where prison staff live and spend time. Without negating the importance of understanding the implications of incarceration for the public health of the systematically disadvantaged communities that lose residents to prison, our research shows that prisons also can lead to negative public health consequences for the people who work in those facilities and their communities. In contrast to the consequences of mass incarceration for the economic health or political power of residents of the places prisons are and the places prisoners come from, any policy intervention that minimizes the role of prisons as vectors of disease transmission may be an area where the interests of both groups are aligned.

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Investigation: YZ

Visualization: YZ, MKC

Funding acquisition: EO, MKC

Writing – original draft: YZ, KT, NS, EO

Writing – review & editing: YZ, KT, NS, EO, MKC

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Data and materials availability: All data, code, and materials used in this analysis are available in anonymized form to any researcher for purposes of reproducing or extending the analysis. Code to produce these data from base data are available, and base data are publicly available subject to purchase and data agreement from Veraset. Data from LODES are publicly available from the U.S. Census Bureau.

Supplementary Materials

Methods: Measure prison-zip code connectivity. We measure prison-zip code connectivity by combining smartphone location data with prison boundary data from the Department of Homeland Security (DHS), with a focus on the 35 state prisons operating in California in 2020. Given the restrictions on cell phone usage within prison facilities, we expand the prison boundary to include neighboring geohash-7 (a 153m * 152 m grid) areas covering the prison boundary. In other words, we define "expanded prison boundary" as all geohash-7s covering both the prison fence line and adjacent spaces, which usually are parking lots (and sometimes highways, see Appendix Figure S1, for example). It is worth noting that the probability of misidentification is minimal, as California state prisons are typically situated in rural areas and well-separated from other infrastructures.

To identify prison staff, we look for cell phones that pinged within the expanded prison boundary for a minimum of 10 minutes in a day. This allows us to filter out transient traffic such as individuals merely driving past the highway nearby. Among the identified phones, we extracted all their smartphone pings, discretizing them to a geohash-7 X half-hour intervals, with each observation representing the geohash-7 where a phone spent at least 10 minutes within a 30-minute time window. We link geohash-7s to zip codes based on their centroid and define the phone's home zip code as the zip code that the phone spent the most time when outside of the expanded prison boundaries during June to October 2020. We measure the connection between a prison and a zip code by calculating the total hours that all cell phones from a specific zip code spent within a particular prison. Essentially, a zip code is considered connected to a prison during a specific period if any phones from that zip code have spent time in San Quentin. Figure 1 maps out the total connectivity to all 35 state prisons for all zip codes.

We replicate our analysis using the LEHD Origin-Destination Employment Statistics data (LODES) from the Census Bureau, which provides information detailing the number of jobs for each home-workplace census block pair. This allows us to identify the home location of prison staff and create an analogous connectivity measure between San Quentin state prison and zip codes. Specifically, we calculate the total primary jobs for individuals working in the block group encompassing San Quentin state prison in 2020 and residing in different census tracts.[1] We then aggregate the tract-level job to the zip code level using a census tract-zip code crosswalk based on the proportion of the tract's population within each ZCTA. Similarly, a zip code is considered connected to a prison if it has workers employed at the San Quentin state prison.

While LODES offers detailed spatial data on origin-destination workflow that enables research on disease transmission, it has limitations compared to smartphone location data. LODES data may reflect the administrative rather than actual worksite location (Graham et al., 2014); it is released annually and may lack precision about the timing of geographic movements. Additionally, specific to this study, it does not account for the remote work among staff during the COVID-19 pandemic. All these data concerns could potentially complicate the inferences about the impact of connectivity between prisons and local communities.

Empirical Strategy. We investigate the public health impact of these prison-zip code connectivity by exploiting an exogenous COVID-19 outbreak in San Quentin state prison in June 2020 due to a prisoner transfer from California Institution for Men. We examine whether the outbreak in San Quentin led to a differential increase in COVID-19 case rates—collected from California Department of Public Health (CDPH)—in zip codes that were connected to San Quentin prison (i.e., treated zip codes) compared to those without this connection (i.e., control zip codes).[2]

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[1] The boundary of the block group containing San Quentin state prison closely matches the boundary of San Quentin itself.

[2] Technically, the COVID case rate data is at the ZIP code level, which we matched to ZCTAs using the ZIP code-ZCTA crosswalk provided by the department of Housing and Urban Development (HUD). In cases where a single ZCTA is associated with multiple ZIP codes (representing less than 2% of the observations), we use the maximum COVID case rate among these zip codes.

We follow Callaway and Li (2023) and estimate the effect of connecting to San Quentin prison after its outbreak in June 2020 using a unconfoundedness-type of strategy that conditions zip codes on pre-transfer COVID-19 variables. This strategy is motivated by the non-linear dynamics of COVID-19, and therefore, traditional difference-in-difference estimates may introduce bias due to different initial COVID-19 conditions between treated and control zip codes. Specifically, this strategy combines an inverse probability weighting approach (i.e., weighting the control zip codes based on the estimated propensity score based on pre-transfer covariates) and an outcome regression approach (i.e., estimating change in the outcome among control zip codes conditioned on the same set of covariates, and averages over the distribution of covariates for treated zip codes to estimate the ATT). The estimates under this strategy are consistent if either the model for propensity score or outcome regression is correctly specified (i.e., doubly robust) (Sant'anna and Zhao, 2020).

We first match treated and control zip codes solely on pre-transfer COVID-19 variables, including the cubic polynomial functions of the number of cases in May 2020, cumulative cases in May 2020, and the logarithm of zip code population (from 2015-2019 American Community Survey (ACS)). In another specification, we match on more demographic characteristics, again from 2015-2019 ACS, in addition to the above pre-transfer COVID-19 variables, including percentages of Black, White, and Hispanic residents; the percentage of residents with a college degree; median household income; and the percentage of residents above age 65. Figure S2illustrates propensity score distributions before and after weighting for treated and control zip codes, and we see that the distribution for the propensity score is nearly identical after the weighting. In a similar vein, Table S1 suggests that the pre-treatment COVID-19 and socioeconomic characteristics are balanced after the weighting adjustment.

Notably, our findings are quantitively similar under alternative specifications. To account for variations in COVID-19 transmission by demographics, in Appendix Table S3, we include interactions between pre-transfer COVID-19 variables and demographic variables for matching in addition to the existing covariates. In Appendix Table S4, S5 and S6 we find consistent estimates when excluding zip codes containing prisons or zip codes that are linked to other prisons that had reported COVID-19 outbreaks before June 2020 (e.g. Avenal state prison and Chuckawalla Valley state prison), mitigating concerns that the results are driven by these specific zip codes. Moreover, our results are robust to alternative definitions of treated groups. For instance, we define connection in June 2020 using varying time spent cutoffs in Appendix Table S7 and S8 and in Appendix Table S9 we define treated groups based on pre-period connection in March 2020 to May 2020 instead of connection in June 2020. In Appendix Table S10 and S11, we report estimates from alternative estimators in addition to the doubly robust estimators, including the inverse propensity weighting and outcome regression. In Appendix Table S12, we replicate results when defining home zip code using the zip code where the phone spent the most time during January to October 2020. Finally, in Appendix Table S13, we report results on the disease transmission when connecting to Corcoran state prison that experience a smaller COVID-19 outbreak.

Additional Materials and Methods are found in the Supplementary Appendix.