COVID-19 in Missouri Prisons and Jails

Appendix 1: Report on the Impact of Mass Incarceration on Covid-19 Outcomes in Missouri

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ABSTRACT

Prisons, jails, and other types of detention centers have long been implicated in the efficient spread of infectious diseases (see Johnson and Raphael 2009; Wakefield and Uggen 2010; Wildeman and Muller 2012; Wildeman and Wang 2017). In the case of COVID-19, prisons, like other group quarters (e.g., nursing homes and college dormitories) have seen elevated cases and deaths (Saloner et al. 2020). Also, multiple features of the corrections system make it an amplifier of COVID-19 spread both within and outside detention walls. This report analyzes publicly available data on COVID-19 infections and deaths in Missouri communities containing prisons and compares it to data from communities that do not contain prisons to gauge whether the COVID-19 risks inherent to prisons put wider communities at risk. The results of our analysis suggest that prison incarceration, measured in various ways, increases the risk of COVID-19 infections in Missouri and that rural, low-income and racial or ethnic minority communities may be particularly vulnerable.

1. Background

1.1. Features of the US Corrections System that Increase Exposure to and Risk of COVID-19 Infection

Prisons, jails, and other types of detention centers have long been implicated in the efficient spread of infectious diseases (see Johnson and Raphael 2009; Wakefield and Uggen 2010; Wildeman and Muller 2012; Wildeman and Wang 2017). In the case of COVID-19, prisons, like other group quarters (e.g., nursing homes and college dormitories) have seen elevated cases and deaths (Saloner et al. 2020). Also, multiple features of the correction system make it an amplifier of COVID-19 spread both within and outside detention walls.

The National Academies of Sciences, Engineering, and Medicine Committee on Best Practices for Implementing Decarceration as a Strategy to Mitigate the Spread of COVID-19 in Correctional Facilities outlined five particularly important features of corrections systems that increase exposure to and risk of COVID-19 infection (Wang et al. 2020; see also United Nations 2020). First, because of the high rate of incarceration in the United States, there are high rates of admission and release, especially in jails, as well as high rates of movement between and within prison facilities. Because of these high rates of movement, COVID-19 can easily spread from the outside-in when infected individuals enter jails and prisons, from the inside-out when infected individuals and correctional staff return to communities, and within and across prison and jail systems when individuals move to different units within a facility or move to different facilities. The risk of infection is amplified in jails and prisons even when stays are short due to living and working in close quarters, limited outdoor time, and contact with potentially infected staff even when socially isolated.

Second, because of the rapid growth in prison and jail populations, facilities are often old, poorly ventilated, and overcrowded. Overcrowded spaces limit the ability to move individuals who have been exposed to or infected with COVID-19 into quarantine or medical isolation. Fixed cell spaces, small congregate areas, and limited numbers of bathrooms and sinks make it nearly impossible to socially distance and keep areas clean and disinfected. Limited access to cleaning products and poor ventilation further compound risk.

Third, admission to and release from jails and prisons are geographically concentrated in predominantly Black and Latinx, low-income neighborhoods. This means that communities already struggling with high rates of COVID-19 infection and chronic disease are exposed to more risk from the inside-out as individuals are released from incarceration. In addition, exposed corrections staff may serve as mechanisms of transmission as they return to and from facilities daily, and staffing shortages due to illnesses and vacancies may prevent staff from limiting exposure to residents infected by COVID-19 in jails and prisons.

Fourth, currently incarcerated persons and people at greatest risk of incarceration are also in poor health, disproportionately burdened by chronic physical and mental health conditions that put these populations at increased risk of severe illness from COVID-19 infection and increased risk of death from COVID-19 infection. Fifth, the correctional health care system is not resourced to manage pandemic outbreaks and is largely siloed from public health and emergency preparedness planning. The former means there is limited staff, resources, and supplies within facilities to manage COVID-19 outbreaks within prisons and jails. For those systems that rely on community-based medical resources and hospitals for assistance, they are likely further stressing community health systems during a pandemic. This can be especially problematic in isolated and/or low-income communities, which include vulnerable populations in need of care with limited community health systems as well as rural communities with finite community health systems.

1.2 Decarceration as a Strategy to Reduce Exposure to and Risk of COVID-19 Infection

"Decarceration is the process of reducing the number of people in correctional facilities by releasing those currently incarcerated and by diverting those who might otherwise be incarcerated. This process involves strategies for ending custodial sentences for those who are incarcerated as well as minimizing arrests, court appearances, and parole and probation revocations for those still in the community" (Wang et al. 2020, p. 1-4). Early experiences with the COVID-19 pandemic and other epidemics (Beaudry et al. 2020) have provided important evidence of the need to depopulate congregate working and living areas, especially high-risk settings such as correctional facilities, to reduce the spread of infection. As discussed earlier, many US correction facilities are overcrowded (Carson 2020) and have additional features, such as poor ventilation and lack of outdoor space, that can spread infection. Indeed, a growing body of evidence suggests that "...decarceration can protect medically vulnerable incarcerated people and staff and "flatten the curve" of virus transmission both within correctional facilities and in the broader community" (Wang et al. 2020, p. 1-4).

To be sure, decarceration efforts across several jurisdictions in the US are already underway as a response to the pandemic. In the first half of 2020, prisons and jails experienced an approximately 11 percent decline in the total incarcerated population (Franco-Paredes et al. 2020; Jail Data Initiative 2020) due to releasing individuals who were close to their release date or considered low risks to public safety and changes to custodial sentencing decisions and intake processes. Some localities have reduced jail admissions by opting for citations instead of arrest or by vacating warrants for unpaid court fines and fees (UCLA Law 2020, Wang et al. 2020).

However, declines have been procedurally slow and not at the pace needed for crises such as a pandemic. Policymakers, correctional officials, correctional and community health providers, and public health officials at the federal, state, and local levels need accurate and detailed information about the role of correctional institutions in the spread of COVID-19 in local areas to make informed decisions about efforts to reduce COVID-19 spread in prisons and surrounding communities, including, but not limited to, decarceration.

1.3 Contributions of this Study

The objective of this report is to analyze publicly available data on COVID-19 infections and deaths in Missouri communities containing prisons and compare it to data from communities that do not contain prisons to gauge whether the COVID-19 risks inherent to correctional facilities put wider communities at risk. A recent report from the Prison Policy Initiative using national data shows that the size of the incarcerated population and the incarceration density (i.e., the number of incarcerated persons per square mile in a given county) of a given county facilitates the spread of COVID-19 to surrounding communities (PPI 2020). That is, as the number of people incarcerated and the incarceration density of an area increases, COVID-19 will spread more efficiently to areas surrounding a prison by way of prison employee commuting patterns, admissions, and releases from correctional institutions, and other behaviors or conditions outlined in the Background section of this report.

Here, we build upon the recent report by PPI with a specific focus on Missouri. While our analysis will be similar to the PPI analysis in many ways, our analysis also has several advantages. First, we make use of more precise (i.e., facility-specific) and more recent state and federal prison population data from 2012 (BJS 2020a). The PPI report uses data on the county-level rate of jail and prison incarceration reported on the 2010 decennial census. While these data and the findings from PPI are informative, we are interested in a different concept: the physical location of prisons in Missouri communities and, relatedly, the size of the incarcerated population in prisons in those communities. Second, we include additional control variables not included in the PPI report that further clarify the association between incarceration density and COVID-19 in surrounding communities, including the proportion of the population currently employed in service occupations and the proportion of the population who primarily commute to work using public transportation.

Third, we use case-control comparisons of Missouri counties with similar demographic, economic, and health characteristics that contain prisons relative to those that do not to further clarify and contextualize the association between prison incarceration and COVID-19 in Missouri. Finally, we conduct a comprehensive series of robustness checks and sensitivity analyses to provide additional confidence in our primary regression models (described in the Materials and Methods section of this report), including model re-estimation using alternative measures of prison incarceration from different years and data sources, re-estimation using measures of jail incarceration, adjusting our measures of prison incarceration for the average rate of decarceration in Missouri from 2012 to 2019, and using alternative geographies to investigate community spread across counties.

2. Materials and Methods

2.1. Outcomes

Our analysis includes three county-level health outcomes: the COVID-19 infection rate (IR), the COVID-19 case fatality rate (CFR), and the COVID-19 crude mortality rate (CMR). Formulas for the outcomes are as follows:

$$\textit{Infection Rate per 1,000 residents} = \frac{\textit{COVID-19 Cases}}{\textit{Total Population}} \times 1{,}000$$

$$\textit{Case Fatality Rate per 100 cases} = \frac{\textit{COVID-19 Deaths}}{\textit{COVID-19 Cases}} \times 100$$

$$\textit{Crude Mortality Rate per 1,000 residents} = \frac{\textit{COVID-19 Deaths}}{\textit{Total Population}} \times 1{,}000$$

2.1.1 Numerator Data for the Outcomes

Data for the numerators come from the New York Times (NYT 2021). Starting with the first COVID-19 case in Washington State on January 21, 2020, NYT has been compiling up-to-date information on COVID-19 cases and deaths at the national, state, and county levels.[4] Briefly, the NYT data collection methodology triangulates data from state or county health departments, data briefs, news conferences, and other sources to identify laboratory-confirmed and probable cases of COVID-19, providing corrections when necessary.

For this analysis, we make use of the county-level COVID-19 data made publicly available by NYT. Two cities in Missouri, Joplin and Kansas City, report COVID-19 data separately and span several counties. As such, we assign all cases and deaths for Joplin and Kansas City to Jasper and Jackson County, respectively. We do so because the majority of each city lies within these respective counties. Data were extracted from the NYT database on January 1st, 2021, and the last daily cumulative totals recorded for each county are from December 31st, 2020. That is, we include all cases and deaths recorded in 2020 for each county in our analysis.

4 Aggregate case and death counts from NYT do not distinguish between cases and deaths among people who are incarcerated and those who are not. Therefore, we are unable to systematically determine if the case and death totals for each county include people who are incarcerated. However, since the NYT data draws on county health department data, and prison data are not usually recorded in county-level health metrics, we have some confidence that this will often be the case for these data as well. In addition, the PPI (2020) nationwide analysis on incarceration and COVID-19 community spread uses the same outcomes. If we perform a crude subtraction of inmate cases from the case counts for each county (see MODOC 2021) and re-estimate our regression models, we still find a positive association between each measure of prison incarceration (described below) and the COVID-19 infection rate.

2.1.2 Denominator Data for the Outcomes

Data for the denominator varies by outcome. For the CFR, data for the denominator (i.e., the total number of COVID-19 cases in a given county) are also derived from the NYT database. For the remaining outcomes, data for the denominator comes from ACS 5-year population estimates, made publicly available from the Integrated Public Use Microdata Series (IPUMS; Ruggles et al. 2020). For the IR and CMR, we use ACS 5-year estimates from 2015-2019 to measure the total population in a given county. ACS 5-year estimates provide a reliable estimate of population counts as well as relevant socio-demographic indicators at smaller areas of aggregation (US Census Bureau 2021). For rural and sparsely populated areas in Missouri, these 5-year estimates are the best available recent data source.

2.2 Prison Incarceration Exposures

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2.2.1 Prison Locations

Our first, binary exposure variable is the presence or absence of one or more state or federal prisons in a given county[5]. Data on the location of state prisons come from the Missouri Department of Corrections (MODOC 2020). Data on the location of the single federal prison in Missouri, the Medical Center for Prisoners Springfield, comes from the Federal Bureau of Prisons (BOP 2020). We locate correctional facilities within counties using street addresses provided by MODOC and BOP. For addresses in cities or towns that spanned multiple counties, we assign facilities using zip codes. For the current analysis, we restrict the exposure to adult correctional institutions, excluding probation and parole offices.

2.2.2 Prison Populations

Our second, continuous exposure variable is the number of people incarcerated in each facility. Current data on the population of each prison, state or federal, is not widely available. As such, we use data from the 2012 Census of State and Federal Adult Correctional Facilities (BJS 2020a), the most recently available census of state and federal prisons in the US[6]. Using these data, we create a continuous measure of the total prison population in each county. For counties that contain several prisons (e.g., Callaway, Cole, and St. Francois), we combine the prison population at all locations for this exposure.

2.2.3 Incarceration Density

Our third, continuous exposure variable is the incarceration density of a given county. Following the methodology by PPI (2020), we calculate the number of incarcerated people per square mile. Data for the numerator comes from the 2012 Census of State and Federal Adult Correctional Facilities (BJS 2020a), and we again combine the prison population at all locations for counties with more than one state or federal prison. Data for the denominator, total county land area in square miles, comes from the 2010 decennial census (US Census Bureau 2020). This measure of incarceration density allows us to compare our results to those in the PPI report.

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5 Missouri has 114 counties and one independent city, St. Louis, which we treat as "county" as well. (N = 115)

6 One facility, the Kansas City Reentry Center, was established in place of a parole center in 2015 and therefore, data on this facility is not available in the 2012 census. Instead, we impute the population of this facility at its capacity, 405.

2.3 Covariates

We also control for several known or probable confounding variables. Using 2015-2019 ACS 5-year estimates, we produce the following county-level demographic and economic characteristics: population density[7], the proportion of the population 65 years of age or older, the proportion Non-Hispanic white alone population, the proportion of households living below the poverty line, the proportion of workers in service occupations, the proportion of the population that uses public transportation to commute to work, and the proportion of the population that is uninsured. Following PPI (2020), we also include several county-level health metrics. Using data from the Robert Wood Johnson Foundation (2020), we produce measures of life expectancy and diabetes prevalence. All health metrics are from 2019 and are intended to capture mortality and morbidity, respectively. For a full description of data sources for all variables, including covariates, see Table 1.

Table 1. Information on Data Sources

Variable	Source
Outcomes	
COVID-19 Infection Rate	New York Times 2020
COVID-19 Case Fatality Rate	New York Times 2020
COVID-19 Crude Mortality Rate	New York Times 2020
Predictors	
Prison Locations	MODOC 2020; BOP 2020
Prison Population	BJS 2012
Incarceration Density	BJS 2012; US Census 2010
Controls	
Population Density	ACS 5-year estimates 2014-2019; US Census 2010
Proportion 65+	ACS 5-year estimates 2014-2019
Proportion Non-Hispanic white	ACS 5-year estimates 2014-2019
Proportion Disabled	ACS 5-year estimates 2014-2019
Average Household Size	ACS 5-year estimates 2014-2019
Proportion Poor	ACS 5-year estimates 2014-2019
Proportion Service Workers	ACS 5-year estimates 2014-2019
Proportion Public Transit	ACS 5-year estimates 2014-2019
Proportion Uninsured	ACS 5-year estimates 2014-2019
Life Expectancy	RWJF 2019
Diabetes Prevalence	RWJF 2019

7 Data for the denominator, total land area in square miles, comes from the 2010 decennial census.

2.4 Analytic Strategy

Our analysis proceeds in three steps. First, we provide a descriptive summary of our data for all counties in Missouri, counties with prisons, and counties without prisons. For this initial step, we perform two-sample t-tests for differences in the outcomes and covariates between counties with and without prisons.

Next, we estimate a series of generalized linear models for each outcome[8]. We estimate models for each exposure variable separately, starting with the binary indicator for prison locations. In Model 1, we estimate the bivariate association to determine if counties with prisons have higher rates of the outcomes than counties without prisons. Model 2 adds controls for county demographic characteristics: population density, the proportion of the population 65 years of age or older, the proportion Non-Hispanic white alone population, the proportion of the population with at least one disability, and the average household size. Model 3 controls for the economic characteristics of the county: the proportion of households living below the poverty line and the proportion of workers in service occupations. Model 4 introduces a control for the proportion of the population that uses public transportation to commute to work. The fully-adjusted model, Model 5, introduces controls for the health environment: the proportion of the population that is uninsured, life expectancy, and diabetes prevalence. This modeling strategy will help identify what characteristics account for any differential patterns in the outcomes across counties.

Lastly, we provide case-comparisons for three matched county pairs. For each comparison, we match a county that contains at least one prison to a county that contains no prisons based on select demographic, economic, and health measures used in the regression analyses. Using principal components analysis, a data reduction technique (Abdi and Williams 2010), we determine that the following variables explain the majority of the variation in demographics, economics, and health across counties in Missouri: population density, the proportion 65 and older, the proportion non-Hispanic white, the proportion living in poverty, the proportion with at least one disability, the proportion using public transportation, and life expectancy. We then sum the differences between these factors for each "case" (i.e., each county in Missouri with a prison) and all possible "controls" (i.e., all counties in Missouri without a prison) and select the control with the smallest difference between a case. Due to space constraints, we highlight three exemplary cases: 1) the county containing a prison with the largest population, Jackson County, 2) the county containing a prison with the median population, Texas County, and 3) the county containing a prison with the smallest population, Mississippi County, as well as their respective controls (St. Charles, Madison, and Dallas). This comparison provides a more contextual, nuanced, and descriptive analysis of the consequences of incarceration for the spread of COVID-19 in Missouri.

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8 Generalized linear models (GLMs) are a family of regression models that utilize maximum likelihood estimation techniques to generate point estimates (regression coefficients) and measures of uncertainty (standard errors). When the distribution of the outcome variable approximates a normal distribution, as is the case for the COVID-19 IR in Missouri, estimates produced using GLMs are equivalent to those produced from ordinary least squares (OLS) regression. However, when the distribution of the outcome is continuous and skewed, as is the case for the COVID-19 CFR and CMR in Missouri, the assumptions of OLS are violated. GLMs relax these assumptions and allow for model estimation when continuous outcomes are skewed. For further discussion of GLMs, see Faraway (2016).

2.5 Covariate Selection, Sensitivity Analyses, and Limitations

Model covariates were selected based on theoretical understandings of the factors that may contribute to the outcomes as well as those that are often confounded with mass incarceration (e.g., use of public transportation, service economics, racial and ethnic composition). In addition, we chose covariates that were used by PPI (2020) to both validate our models and make comparisons between our estimates and theirs.

However, our model specifications differ from those by PPI in several ways. First, PPI includes more specific information on racial and ethnic composition as well as the proportion of the county that is foreign-born. Here, we only include the proportion of the county that is non-Hispanic white because of the high correlation between racial composition, ethnic composition and nativity status across Missouri counties. Put differently, there simply isn't enough variation in the racial and ethnic or nativity composition of Missouri counties to warrant predictors for each combination of race, ethnicity, or nativity used by PPI. For similar reasons, we only include the proportion of the population living in poverty rather than including additional measures for median household income or educational attainment.

We also chose to exclude several variables that were used in the PPI report, including information on the number of people detained by Immigration and Customs Enforcement (ICE), urbanity or rurality, residents in nursing homes, residents in other group quarters, and whether or not the county contains a meatpacking plant that experienced a COVID-19 outbreak. While our reason for these exclusions varies slightly for each measure, in general we chose to exclude these measures because the data is sparse, unreliable, or outdated relative to the other measures in our model. For example, because we use data from the 2019 ACS 5-year estimates, a more recent data source, information on the number of residents in nursing homes and other group quarters is not available. This information is only including on decennial censuses. Likewise, the data for outbreaks at meatpacking plants is sparse and unreliable. As such, we decided not to introduce these data to limit uncertainty and unknown biases in the models. We have similar reasons for excluding information on ICE detainees. Lastly, other measures in our models capture aspects of urbanity or rurality that are of interest (e.g., public transportation use, population density) and the inclusion of a binary indicator for urbanity or rurality would be redundant.

We perform several sensitivity analyses to test the robustness of our estimates. First, we re-estimate our regression models using a series of alternative exposures, including data on the rate of incarceration by sentencing county from 2016 (Vera Institute of Justice 2020) and 2019 (MODOC 2019) as well data on the rate of jail incarceration from 2018 (Vera Institute of Justice 2020). Briefly, the results of these models show no statistically significant association between the size of the incarcerated population in a county or the incarceration density of a county, although the associations were positive, as expected. While PPI (2020) used a similar measure in their analyses, the null findings from this sensitivity analysis are not necessarily unexpected, considering that people incarcerated in prisons are likely to be incarcerated in counties other than the one they were sentenced in. This will be especially true for women, as there are only two prisons housing female inmates in Missouri. For the alternative measures of jail incarceration, the positive but not statistically significant associations may be due to the uncertainty of jail incarceration estimates or the instability of these populations. Furthermore, measures such as this capture fundamentally different concepts (e.g., criminality, criminal legal surveillance) than the one we are interested in here: the physical structure of prisons and the concentration of individuals within these facilities.

Second, we re-estimate our regression models using the same exposures from 2012 but adjusting our measures of the prison population and incarceration density for the average rate of decarceration in Missouri between 2012 and 2019. In 2012, Missouri had a total of 31,247 people incarcerated in state or federal prisons. By 2019, this total had decreased to 26,044, approximately 83% of the incarcerated population in 2012 (BJS 2020b; author calculations using CSAT). Accordingly, we reduce the population at each facility to 83% of the 2012 population and find that the associations presented in the results below hold: they are positive and statistically significant. However, we choose to present the results using the 2012 BJS data because they are more accurate and because rates of decarceration may not be similar across all facilities in Missouri.

Third, to support our findings on prison incarceration and COVID-19 community spread, we draw on the PPI (2020) methodology and perform supplemental analyses using an alternative aggregation: 2010 multicounty United States Department of Agriculture (USDA; Fowler et al. 2016) commuting zones (CZs)[9]. For this analysis, we included all CZs that contained at least one Missouri county and measures of prison incarceration excluded each county's own prisons or prison populations. That is, for each CZ, we aggregated the number of prisons, the prison populations, and the incarceration density of every other county in the CZ, but did not count those held in the county itself. By doing so, we can further examine how the prisons and prison populations held in other, nearby counties may have contributed to the spread of COVID-19 in a given county. In addition, this analysis acknowledges that counties are permeable: people can and do commute across neighboring counties for various reasons. Briefly, these supplemental analyses show that as the number of prisons, the number of total people incarcerated, and the density of incarceration in a CZ increases, so does the COVID-19 IR. Associations between prison incarceration and the remaining outcomes were not robust across model specification and/or the associations did not reach statistical significance, consistent with our primary analysis. This supplement suggests COVID-19 community spread in CZs with more prisons, with more people incarcerated in prisons, and with greater incarceration density.

Lastly, the analysis should be interpreted with the following limitations in mind. First, our unit of analysis is the county and, as such, we are not able to generalize to individuals within these counties nor are we able to calculate infection rates (R_0) within correctional facilities or within counties. Second, we are not able to observe all potentially relevant covariates in the ACS or the data from RWJF. For example, neither data source contains county-level data on asthma prevalence, a chronic respiratory condition that may put some people at a higher risk of death than others. Other limitations of ACS data have been described above. Fourth, and relatedly, while the 2012 BJS prison population data are more granular and recent than the 2010 decennial census data on county-level incarceration rates, more recent data would be ideal. However, these are the most recent prison census data available. In addition, our decarceration robustness check,

9 While PPI's (2020) nationwide analysis uses 2004 Bureau of Economic Analysis economic areas (BEAs; Johnson and Kort 2004) instead of 2010 USDA CZs, BEAs may not be suitable for a state-specific analysis, particularly in states like Missouri which are largely comprised of rural areas save for a few metro- or micro-politan areas, many of which exist on the borders of the state. BEA delineations center on metro- or micro-politan areas and rely on newspaper readership in less populated areas to identify connections between counties. In contrast, USDA CZs are identified using hierarchical cluster analysis to determine common commuting patterns, regardless of whether counties surround metro- or micro-politan areas (see ERS 2019 for more details). In addition, CZ delineations are more recent and based on 2010 US Census data, while BEAs are based on Census data from 2000.

described above, shows that these trends hold assuming a uniform pattern of decarceration across prisons in Missouri. Fifth, there are several limitations for the NYT data that have been noted in this report and summarized in greater detail elsewhere (Benchaabane 2020, NYT 2021). Lastly, given the cross-sectional nature of the data and analysis, we cannot make causal claims based on our findings. However, this work can inform how to understand differences in COVID-19 risk in places that do and do not contain prisons.

3. Results

3.1 Descriptive Summaries and Tests of Heterogeneity

Descriptive statistics for the sample are shown in Table 2, along with the results from two-sample t-tests for heterogeneity between counties that contain prisons and counties that do not. Results in Table 2 show that the average COVID infection rate for counties in Missouri is 73.83 cases per 1,000 residents. As a reminder, these case totals are cumulative and reflect the average total cases for counties in Missouri. Still, this infection rate is noteworthy, as previous analyses by Drs. Larimore and Lee published in July 2020 showed a maximum infection rate of 11.73 cases per 1,000 residents across Missouri counties (Lee et al 2020; see also, Prener 2020). This shift in infection rates in five months underscores the severity of COVID-19 infections in Missouri. In addition, results of the two-sample t-test show that counties containing at least one prison have significantly higher COVID-19 infection rates than counties that do not contain a prison. The low p-value shown in the last column of Table 2 suggests that the probability that this difference occurred by chance (i.e., that it is not a true difference) is less than 1 in 1,000.

For the remaining outcomes, we find no statistically significant differences between counties that contain prisons and those that do not. Also, we find few differences in the covariates between counties that contain prisons and those that do not. The only statistically significant difference we find suggests that counties without prisons have more residents aged 65 years or older than counties with prisons. Otherwise, counties in Missouri have similar demographic, economic, and health characteristics regardless of whether they contain a prison or not.

3.2 Regression Analyses

As described above, our modeling strategy estimates five consecutive models for each exposure, outcome combination, introducing new covariates in each model. This modeling approach produces 45 separate regression analyses, 15 for each outcome[10]. For simplicity, we only present the estimates for the exposure in the tables below, but full regression estimates are available in Appendix A.

10 In regression analysis involving multiple hypothesis tests, multiple comparison is a commonly cited problem. In short, the multiple comparison problem argues that, as the number of simultaneous tests increases, so does the risk of Type I error or false positives. However, as Gelman and Hill (2007) note, "[there] is no need to correct for the multiplicity of tests if we accept that they will be mistaken on occasion". Indeed, this is the nature of inferential statistics. Therefore, we contend that this is a non-issue but also note that post-hoc corrections, including the conservative Bonferroni correction, validate the results presented here.

Table 2. Descriptive Statistics for Missouri Counties by Prison Locations

	All Counties	Counties without Prisons	Counties with Prisons	p-value
COVID-19 Outcomes				
COVID Infection Rate	64.97	**62.44**	**77.75**	**0.0004**
COVID Crude Fatality Rate	1.47	1.46	1.52	0.7530
COVID Crude Mortality Rate	0.95	0.91	1.14	0.0972
Control Variables				
Population Density	140.56	139.76	144.59	0.9568
Proportion 65+	19.23	**19.73**	**16.69**	**0.0000**
Proportion Non-Hispanic white	90.26	90.79	87.56	0.1321
Proportion Disabled	17.66	17.98	16.04	0.0879
Average Household Size	2.50	2.50	2.48	0.5582
Proportion of Households Living in Poverty	16.22	16.29	15.88	0.7352
Proportion of Workers in Service Occupations	17.97	17.89	18.36	0.522
Proportion Using Public Transportation	0.76	0.74	0.87	0.6586
Proportion Uninsured	11.61	11.77	10.81	0.1936
Life Expectancy	76.66	76.63	76.81	0.6871
Diabetes Prevalence	12.79	12.89	12.32	0.0789
Sample Size	***115***	***96***	***19***	
Note: Statistically significant differences ($p < 0.05$) shown in bold.				

3.2.1 COVID-19 Infection Rate

Results from the regression analysis estimating the association between the exposures and the COVID-19 infection rate are shown in Table 3. In general, the results in Table 3 show that prisons correspond to an increase in the rate of COVID-19 infections in Missouri and that this association is robust to differences in the measurement of incarceration and persists once likely confounders have been accounted for. For the association between prison locations and COVID-19 infections, we find that even when all demographic, economic, and health characteristics have been accounted for (Model 5), counties with prisons are expected to have nine more COVID-19 cases per 100,000 residents than those that do not.

Similarly, we find that the size of the incarcerated population also increases the rate of COVID-19 infections. While the effect of size may appear small and not substantively meaningful, it is important to note that each additional person who is incarcerated represents a one-unit increase in the exposure. That is, each additional person incarcerated in a state or federal prison increases the rate of COVID-19 infection by 0.005 (Model 5). Put differently, adding 200 inmates to a state or federal prison would add one additional infection to that county. We find a similar association between incarceration density

Table 3. Associations between Prison Incarceration and COVID-19 Infection Rates

	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Prison Location					
Coefficient	15.3043***	9.9674*	9.8252*	9.7460*	9.8090*
Standard Error	(4.1770)	(4.2389)	(4.2775)	(4.3171)	(4.3480)
Incarcerated Population					
Coefficient	0.0076***	0.0055**	0.0056**	0.0056**	0.0056*
Standard Error	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Incarceration Density					
Coefficient	3.6041***	2.6634**	2.7276**	2.7168**	2.7589**
Standard Error	(0.9367)	(0.9239)	(0.9353)	(0.9400)	(0.9440)
Note:	*$*p<0.05$; $**p<0.01$; $***p<0.001$*				

and COVID-19 infection rates: as the number of incarcerated persons per square mile increases, so does the rate of infection. Using model estimates and holding all covariates at their means, we can predict that a county with no incarcerated people per square mile would have 63 cumulative infections per 100,000 residents, a county with 5 incarcerated people per square mile would have 77 infections, and a county with 12 incarcerated people per square mile (the maximum observed in the data) would have 96 infections (predictions available on request).

3.2.2 COVID-19 Case Fatality Rate

Results from the regression analysis estimating the association between the exposures and the COVID-19 CFR are shown in Table 4. As was the case for infection rates, we find that all measures of the exposure – prison location, incarcerated population, and incarceration density – have a positive association with the outcome. However, these associations are not statistically significant. That is, differences in the COVID-19 CFR between counties with prisons and counties without prisons are likely due to chance, not to the location of prisons, the size of the prison population, or the incarceration density.

Table 4. Associations between Prison Incarceration and COVID-19 Case Fatality Rates

	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Prison Location					
Coefficient	0.0668	0.1596	0.1723	0.1355	0.1250
Standard Error	(0.2072)	(0.2178)	(0.2192)	(0.2181)	(0.2195)
Incarcerated Population					
Coefficient	0.00001	0.00004	0.00004	0.00004	0.00004
Standard Error	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Incarceration Density					
Coefficient	0.0111	0.0233	0.0246	0.0213	0.0195
Standard Error	(0.0467)	(0.0481)	(0.0487)	(0.0482)	(0.0484)
Note:	**p<0.05; **p<0.01; ***p<0.001*				

3.2.3 COVID-19 Crude Mortality Rate

Results from the regression analysis estimating the association between the exposures and the COVID-19 CMR are shown in Table 5. We again find that all measures of the exposure – prison location, incarcerated population, and incarceration density – have a positive association with the outcome. However, as was the case with CFR, these associations are not statistically significant. That is, differences in the COVID-19 CMR between counties with prisons and counties without prisons are likely due to chance, not to the location of prisons, the size of the prison population, or the incarceration density.

Table 5. Associations between Prison Incarceration and COVID-19 Crude Mortality Rates

	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Prison Location					
Coefficient	0.2185	0.2172	0.2220	0.1939	0.1873
Standard Error	(0.1430)	(0.1521)	(0.1534)	(0.1521)	(0.1539)
Incarcerated Population					
Coefficient	0.0001	0.0001	0.0001	0.0001	0.0001
Standard Error	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Incarceration Density					
Coefficient	0.0489	0.0463	0.0493	0.0468	0.0462
Standard Error	(0.0322)	(0.0336)	(0.0340)	(0.0336)	(0.0339)
Note:	**p<0.05; **p<0.01; ***p<0.001*				

3.3 Matched County Case-Control Comparisons

To contextualize the association between prison incarceration and COVID-19 outcomes in Missouri, we provide case-comparisons for three matched county pairs. Matched case-control pairs for all counties containing prisons as well as the three pairs we describe in more detail here are shown in Table 6.

Table 6. Case-Control Matches Comparing Counties with Prisons and Counties without Prisons

Case	Control
Audrain	Ste. Genevieve
Buchanan	Platte
Callaway	Lafayette
Clinton	Polk
Cole	Jasper
Cooper	Saline
Franklin	Pulaski
Greene	Jefferson
Jackson	**St. Charles**
Livingston	Gasconade
Mississippi	**Dallas**
Moniteau	McDonald
Nodaway	Cedar
Pike	Pemiscot
Randolph	Dunklin [11]
St. Francois	Cass
Texas	**Madison**
Washington	Henry
Webster	Johnson

Note: The pairs we highlight here are shown in bold.

11 Polk County was most similar to Randolph County regarding demographic, economic, and health characteristics but since Polk County was already matched with Clinton County, we used the second most similar control county, Dunklin.

3.3.1 Jackson County and St. Charles County

Respectively, Jackson and St. Charles counties are the second- and third-most populous counties in the state. According to the ACS estimates used in this analysis, Jackson County has a population of 696,216 residents, while St. Charles County has a population of 394,290 residents. Geographically, Jackson County sits at the western end of the state, bordering Kansas and sharing Kansas City proper as well as the broader metropolitan area. In contrast, St. Charles County sits at the eastern end of the state, bordering Illinois. St. Charles County is also part of the St. Louis metropolitan area and lies to the northwest of both St. Louis County and St. Louis City. St. Charles County, of course, contains no state or federal prisons while Jackson County houses the Kansas City Reentry Center, a state prison that was established in place of a parole center in 2015 and can house over 400 people.

These counties differ in other notable demographic and economic characteristics. In general, St. Charles County is whiter, wealthier, and healthier than Jackson County. In 2019, an estimated 87% of St. Charles County residents identified as Non-Hispanic white compared to an estimated 62% of Jackson County residents. Likewise, approximately 15% of the population in Jackson County lives below the poverty line, while 95% of St. Charles County residents live above the poverty line. Also, a baby born in St. Charles County in 2019 can expect to live to see their 80th birthday, while babies born in Jackson County can expect to live 77 years.

While these demographic, economic, and health differences are striking, there is less magnitude in the difference of COVID-19 outcomes between the counties. Notably, the CFR for both counties is 1.11 deaths per 100 cases. In addition, the CMR for Jackson County is 0.85 deaths per 1,000 residents, while the CMR in St. Charles county is only slightly lower: 0.83 deaths per 1,000 residents. Put differently, both counties have experienced just over eight COVID-19 deaths for every 10,000 residents. Lastly, the COVID-19 IR in Jackson County is 76.79 cases per 1,000 residents while the IR in St. Charles County is 75.25 cases per 1,000 residents.

Overall, differences in the outcomes between Jackson and St. Charles counties are not substantive and are likely due to chance. However, these minimal differences also speak to the general trend found by PPI (2020) and noted in other reports: urban areas with prisons are not different from urban areas without prisons (see also Florida 2020 for a discussion of population density and COVID-19 infection). Urban areas in Missouri and elsewhere may be better equipped with resources to mitigate the spread of COVID-19. Also, both counties are closer to or contain, geographically, the premier medical institutions in the state (e.g., Barnes-Jewish Hospital in St. Louis City and Saint Luke's Hospital in Kansas City; Olmos 2019).

3.3.2. Texas County and Madison County

Texas County, Missouri is located in the southern portion of the state, east of Springfield and south of Jefferson City. Texas County has an estimated population of 25,604, the median population for all counties containing prisons in Missouri. In addition, Plato, a town in Texas County, was identified by the US Census Bureau as the geographic center of the population in 2010, underscoring the notion that Texas County is a good representation of the "middle" (US Census 2010). Its control, Madison County, is located in the southeastern part of the state, about 60 miles west of Cape Girardeau and the Mississippi River. Madison County is about half the size, both in geographic and population, of Texas County, with 12,179 residents spread over 494.39 square miles.

In some ways, the counties are very similar. Over 90% of the population in both counties identifies as non-Hispanic white, approximately 20% of the residents in each county are employed in service occupations, and about 24% of the population in each county has at least one disability. However, the two counties differ in other, important ways. Specifically, Texas County has more residents living in poverty (25%) and more residents without health insurance (16%) than Madison County (14% and 11%, respectively). In addition, the two counties differ slightly in the length of life experienced by residents as Texas County has a life expectancy of 76.6 years while residents of Madison County have a life expectancy of 73.7 years.

Texas County contains one prison, the South Central Correctional Center, which had a population of 1,600 in 2012 (BJS 2020a). While the overall results from the regression analysis suggest that counties containing prisons will have higher rates of the outcomes and significantly higher rates of COVID-19 IR than counties without prisons, the comparison between Texas and Madison counties shows that these aggregate patterns may not hold for all individual cases. Madison County has higher rates of all outcomes than Texas County. In Madison County, the IR is 98.53 cases per 1,000 residents and the CMR is 0.82 deaths per 1,000 cases. In Texas County, the outcomes are 52.30 and 0.66 respectively. However, the CFR in Texas County is greater (1.27) than in Madison County (0.83), perhaps reflecting that Texas County is, on the whole, sicker and poorer than its counterpart.

While this comparison may run counter to expectations given our regression results, there are several possible explanations for this counterintuitive finding. First, Madison County may not be the best possible match for Texas County. While we believe our matching method is valid and that Madison County is a good comparison, other counties including Grundy, Hickory, Howard, and New Madrid County also share similarities with Texas County. In supplemental analyses, we find that there are lower rates of several of the outcomes in these counties compared to Texas County. Second, Madison County shares a border with St. Francois County, which also contains a prison. Therefore, it is possible that the consequences of prison incarceration in St. Francois County spread to Madison County. Previous research by PPI (2020) has used larger levels of aggregation to show that the association between incarceration and COVID-19 outcomes may be diffuse, spreading to counties with lower levels of incarceration. This may be the case in Madison County as well. Indeed, our supplemental analysis using USDA CZs suggests that this is the case.

3.3.3 Mississippi County and Dallas County

Our last case-control comparisons, Mississippi and Dallas counties, are both rural and sparsely populated. Mississippi County, Missouri is nestled in the “boot heel” of the state along the Mississippi River, bordering Illinois to the north and Kentucky to the east. The population of Mississippi County is an estimated 13,574 residents and the population density of the county is 32 residents per square mile. Mississippi County also contains one prison, the Southeast Correctional Center in Charleston, Missouri. In 2012, the prison had a population of 1,625, slightly above the stated capacity of 1,622 people. Dallas County is just northeast of Springfield, MO and has an estimated 16,617 residents spread across 540.77 miles, making Dallas County slightly less densely populated that Mississippi County (30 residents per square mile). It is worth noting that while Dallas County does not contain a prison, it borders two counties that do: Greene and Webster.

Compared to Dallas County, Mississippi County is poorer and more racially diverse. According to the ACS estimates used in this analysis, 25% of Mississippi County residents are living in poverty and 24% of Mississippi County residents identified as non-Hispanic Black or African American. This is notable, as only nearby Pemiscot County and St. Louis City have a higher share of Black or African American residents (27.17% and 46.23%, respectively). In addition, over 23% of Mississippi County workers are employed in service occupations. In contrast, 18% of Dallas County residents are living in poverty, less than 1% identify as non-Hispanic Black or African American, and 18% are employed in service occupations.

As anticipated, based on the results of the regression analysis, the COVID IR and CMR are higher in Mississippi County than in Dallas County, and this is particularly true for the rate of infection. In Mississippi County, the COVID IR is approximately 84 cases per 1,000 residents while in Dallas County, the COVID IR is approximately 41 cases per 1,000 residents. Differences in the CMR between counties are also present, but they are much smaller. In Mississippi County, the CMR is 1.11 deaths per 1,000 residents while in Dallas County, the CMR is 1.08 deaths per 1,000 residents. While we find the expected association between prison incarceration and these outcomes in our comparison of Mississippi and Dallas, we also find that the CFR is higher in Dallas County than in Mississippi County. Again, this runs somewhat counter to our expectations, but given that the association between prison incarceration and this outcome was positive but not statistically significant, it is not necessarily unsurprising. In Dallas County, the CFR is 2.58 deaths per 100 cases while it is 1.32 deaths per 100 cases.

The comparison between Mississippi and Dallas counties suggests that rural communities, particularly those that are predominately low-income and/or have more residents who identify as Black or African American, may be particularly susceptible to the impacts of prison incarceration on the spread and severity of COVID-19 (see Oppel et al. 2020 for a summary of racial disparities in COVID-19 outcomes). It is important to note that, due to the history of racial oppression in the United States, race and socioeconomic status are deeply intertwined. These overlapping forms of disadvantage are robust predictors of population health (see Williams et al. 2019 for a review). Indeed, as the results in Appendix A show, as the proportion of non-Hispanic white residents in a county increase, the risk of all outcomes decreases, but as the proportion of county residents living in poverty increases, the risk of infection increases. Still, even when these predictors are included in the models, the associations between prison incarceration and the outcomes holds.

4. DISCUSSION

4.1 Summary of Findings

The findings from this report can be summarized as follows. First, the results of the descriptive and regression analyses suggest that the association between prison incarceration and the risk of COVID-19 infection in Missouri counties is positive and statistically significant. This association is robust to various measurements of the exposure including the physical location of prisons, the size of the prison population, and the incarceration density of an area. Reports on the impact of mass incarceration on COVID-19 infection rates have been reported elsewhere (PPI 2020) and align with our findings.

Second, and relatedly, we complement previous research by showing that the *physical location* of a prison increases the risk of COVID-19 infections. That is, while previous research has investigated the association between the *rate of* both jail and prison incarceration in a county and COVID-19 outcomes, our findings suggest that whether a county or CZ contains a prison *at all* influences the spread of COVID-19 in that county or CZ.

Third, our case-control comparison analysis suggests that while urban areas may be able to mitigate the consequences of prison incarceration due to access to infrastructure and resources, rural areas may be more susceptible and that this may be particularly true if their population is low income and/or predominately racial/ethnic minorities. Also, our case-control comparison analysis suggests to a degree that counties that do not contain a prison but that border or are geographically near one or more counties that do contain a prison may also be at an elevated risk, implying community spread. Again, previous research (PPI 2020) and supplemental analysis to this report suggest that this may be true at the national level as well as in Missouri.

4.2 Finding Implications

Our results suggest that strategies to decarcerate prisons may indeed reduce COVID-19 infections, particularly in disadvantaged rural areas. Reducing prison populations will allow for needed social distancing and quarantine practices within prisons, reduce strain on correctional staff, and prevent correctional staff exposure to those isolated because of infection or exposure to COVID-19. In turn, community members where correctional staff reside, especially their families, will also experience a reduced risk of exposure to COVID-19. In addition, the improvement of conditions of confinement, such as improved ventilation and outdoor spaces for recreation, can also reduce risk among those who reside and work in prison, as well as communities via reduced risk among prison staff.

To be sure, as noted by *The National Academies of Sciences, Engineering, and Medicine Committee on Best Practices for Implementing Decarceration as a Strategy to Mitigate the Spread of COVID-19 in the Correctional Facilities* report, decarceration strategies must be coupled with robust community supports for both individuals and the families that many of them return to. They state:

> *"Many of the challenges for meeting basic needs that individuals returning to the community confronted before the pandemic have been exacerbated during the COVID-19 period. The conditions to which individuals return home vary across communities and depend not only on the rates of community viral transmission but also on the available resources and supports for health care, housing, and income. Reentry planning will need to balance these considerations, as well as testing prior to release, the ability to quarantine in the community, and a complement of health care, housing, and income supports, as they are available; they are all important complements to decarceration efforts to maximize individual, family, and community health and safety. Decarceration will be most successful if correctional system leaders collaborate with community health care and social safety net systems to provide support to this population and eliminate barriers to existing resources and programs, including Medicaid, housing programs, and SNAP, which collectively can help mitigate both public health and public safety risks."*
> (Wang et al. 2020; p. 4-12)

Reducing the risk of COVID-19 infection is a public health priority. Understanding the role of prisons in risk for those who live and/or work in prison and the communities that they are connected to is a key to informing policies and practice that coupled with additional efforts can serve to protect and promote health for all populations.

4.3 Conclusion

This report finds that prison incarceration increases the risk of COVID-19 infection in Missouri counties and that these burdens will be felt the most by some of Missouri's most marginalized residents: those in rural areas, those who are low-income, and those who are racial or ethnic minorities. As such, prison incarceration constitutes a primary public health concern for Missourians. Therefore, decarceration may be a worthwhile strategy to decrease the rate of COVID-19 infection in Missouri.

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A. Full Regression Tables and Model Fit Statistics

Table A1. Prison Location and COVID-19 Infection Rate

	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Prison	**15.3043*** **	**9.9674** **	**9.8252** **	**9.7460** **	**9.8090** **
	(4.1770)	*(4.2389)*	*(4.2775)*	*(4.3171)*	*(4.3480)*
Population Density		**-0.0083** **	**-0.0079** **	-0.0093	-0.0098
		(0.0035)	*(0.0036)*	*(0.0081)*	*(0.0082)*
Proportion 65+		-78.9669	-75.4432	-74.8745	-81.5021
		(54.9236)	*(55.6374)*	*(55.9713)*	*(63.4529)*
Proportion Non-Hispanic White		**-56.7714** **	-51.1363	-51.2692	-47.2285
		(28.0970)	*(29.6063)*	*(29.7499)*	*(30.0616)*
Proportion Disabled		-46.9697	-68.8797	-70.0984	-64.5947
		(38.2230)	*(51.4631)*	*(52.0910)*	*(58.1293)*
Average Household Size		-10.3808	-8.5671	-8.4029	-3.7636
		(9.9287)	*(10.4740)*	*(10.5570)*	*(11.6201)*
Proportion Poor			18.8799	16.6158	38.1981
			(40.6221)	*(42.4954)*	*(47.6616)*
Proportion Service Workers			25.6711	26.8526	34.8021
			(61.6531)	*(62.2435)*	*(66.3302)*
Proportion Public Transit				49.6573	87.2515
				(260.0343)	*(263.0023)*
Proportion Uninsured					-45.4120
					(50.1639)
Life Expectancy					0.6370
					(1.1533)
Diabetes Prevalence					0.8333
					(1.2639)
Constant	**62.4429*** **	**165.1225*** **	**150.9996*** **	**150.8018*** **	76.5047
	(1.6978)	*(35.3697)*	*(42.7390)*	*(42.9471)*	*(105.4553)*
Adjusted R-Squared	0.1062	0.2236	0.2266	0.2269	0.2414
Akaike Inf. Crit.	976.9893	970.8005	974.3425	976.3026	980.1214
Note:					*$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$*

Standard errors are shown in parentheses and italics. Statistically significant associations are shown in red. The adjusted R-squared statistic show how much of the variance is explained, but should be interpreted with caution given that the addition of any predictor, regardless of its importance, will increase this statistic. The Akaike's Information Criterion (AIC) assesses comparative model fit and also penalizes overfitting by minimizing information loss. Both should be considered when interpreting model fit.

Table A2. Prison Location and COVID-19 Case Fatality Rate					
	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Prison	0.0668	0.1596	0.1723	0.1355	0.1250
	(0.2072)	*(0.2178)*	*(0.2192)*	*(0.2181)*	*(0.2195)*
Population Density		0.00003	0.000003	-0.0006	-0.0006
		(0.0002)	*(0.0002)*	*(0.0004)*	*(0.0004)*
Proportion 65+		4.5548	4.2601	4.5244	3.8627
		(2.8224)	*(2.8514)*	*(2.8278)*	*(3.2029)*
Proportion Non-Hispanic White		-0.1560	-0.5467	-0.6085	-0.7258
		(1.4438)	*(1.5173)*	*(1.5030)*	*(1.5174)*
Proportion Disabled		-1.2950	0.0118	-0.5546	-1.5227
		(1.9642)	*(2.6375)*	*(2.6317)*	*(2.9342)*
Average Household Size		-0.7200	-0.8782	-0.8019	-0.9999
		(0.5102)	*(0.5368)*	*(0.5334)*	*(0.5865)*
Proportion Poor			-0.4831	-1.5354	-3.0062
			(2.0819)	*(2.1469)*	*(2.4058)*
Proportion Service Workers			-2.9984	-2.4493	-2.2745
			(3.1597)	*(3.1446)*	*(3.3481)*
Proportion Public Transit				23.0782	21.5077
				(13.1374)	*(13.2754)*
Proportion Uninsured					2.8747
					(2.5321)
Life Expectancy					-0.0317
					(0.0582)
Diabetes Prevalence					0.0142
					(0.0638)
Constant	**1.4616***	2.7328	3.9248	3.8329	6.8629
	(0.0842)	*(1.8176)*	*(2.1904)*	*(2.1698)*	*(5.3230)*
Adjusted R-Squared	0.0001	0.0683	0.0769	0.1033	0.1217
Akaike Inf. Crit.	286.1030	288.0777	291.0023	289.6711	293.2841
Note:	**p<0.05; **p<0.01; ***p<0.001*				

Standard errors are shown in parentheses and italics. Statistically significant associations are shown in red. The adjusted R-squared statistic show how much of the variance is explained, but should be interpreted with caution given that the addition of any predictor, regardless of its importance, will increase this statistic. The Akaike's Information Criterion (AIC) assesses comparative model fit and also penalizes overfitting by minimizing information loss. Both should be considered when interpreting model fit.

Table A3. Prison Location and COVID-19 Crude Mortality Rate					
	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Prison	0.2185	0.2172	0.2220	0.1939	0.1873
	(0.1430)	*(0.1521)*	*(0.1534)*	*(0.1521)*	*(0.1539)*
Population Density		-0.0001	-0.0001	**-0.0006***	**-0.0006***
		(0.0001)	*(0.0001)*	*(0.0003)*	*(0.0003)*
Proportion 65+		2.4730	2.3734	2.5757	1.9881
		(1.9704)	*(1.9948)*	*(1.9725)*	*(2.2462)*
Proportion Non-Hispanic White		-1.1783	-1.2621	-1.3094	-1.3283
		(1.0080)	*(1.0615)*	*(1.0484)*	*(1.0642)*
Proportion Disabled		-1.4984	-1.3720	-1.8055	-2.3486
		(1.3713)	*(1.8451)*	*(1.8358)*	*(2.0577)*
Average Household Size		-0.4566	-0.5139	-0.4556	-0.5263
		(0.3562)	*(0.3755)*	*(0.3720)*	*(0.4113)*
Proportion Poor			0.4945	-0.3107	-0.9989
			(1.4564)	*(1.4976)*	*(1.6872)*
Proportion Service Workers			-1.5250	-1.1048	-0.8328
			(2.2105)	*(2.1936)*	*(2.3480)*
Proportion Public Transit				17.6613	17.1825
				(9.1640)	*(9.3100)*
Proportion Uninsured					1.3275
					(1.7757)
Life Expectancy					-0.0101
					(0.0408)
Diabetes Prevalence					0.0227
					(0.0447)
Constant	**0.9174*****	**2.9252***	**3.3348***	**3.2645***	4.0601
	(0.0581)	*(1.2689)*	*(1.5323)*	*(1.5135)*	*(3.7330)*
Adjusted R-Squared	0.0202	0.0648	0.0697	0.1015	0.1105
Akaike Inf. Crit.	200.7887	205.4325	208.8294	206.8317	211.6745
Note:	**p<0.05; **p<0.01; ***p<0.001*				

Standard errors are shown in parentheses and italics. Statistically significant associations are shown in red. The adjusted R-squared statistic show how much of the variance is explained, but should be interpreted with caution given that the addition of any predictor, regardless of its importance, will increase this statistic. The Akaike's Information Criterion (AIC) assesses comparative model fit and also penalizes overfitting by minimizing information loss. Both should be considered when interpreting model fit.

Table A4. Prison Population and COVID-19 Infection Rate					
	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Prison Population	**0.0076***	**0.0055**	**0.0056**	**0.0056**	**0.0056**
	(0.0020)	*(0.0020)*	*(0.0020)*	*(0.0020)*	*(0.0020)*
Population Density		**-0.0083***	**-0.0078***	-0.0104	-0.0109
		(0.0035)	*(0.0036)*	*(0.0080)*	*(0.0080)*
Proportion 65+		-75.7812	-70.9248	-69.5254	-78.7061
		(54.2621)	*(54.9453)*	*(55.3096)*	*(62.4199)*
Proportion Non-Hispanic White		**-58.4705***	-51.4522	-51.6685	-47.5811
		(27.8053)	*(29.2789)*	*(29.4060)*	*(29.7037)*
Proportion Disabled		-52.7909	-81.7249	-83.8665	-77.1032
		(37.8563)	*(50.8732)*	*(51.4297)*	*(57.3918)*
Average Household Size		-9.5431	-7.4828	-7.1419	-2.7932
		(9.8498)	*(10.3843)*	*(10.4703)*	*(11.4978)*
Proportion Poor			30.8842	26.6385	47.3147
			(40.3539)	*(42.2072)*	*(47.3027)*
Proportion Service Workers			20.3388	22.4468	32.4984
			(61.0791)	*(61.6113)*	*(65.5568)*
Proportion Public Transit				92.0092	131.1224
				(255.9798)	*(258.7861)*
Proportion Uninsured					-41.9437
					(49.5164)
Life Expectancy					0.7385
					(1.1391)
Diabetes Prevalence					0.8931
					(1.2485)
Constant	**62.9065***	**165.1145***	**149.0611***	**148.4896***	65.9589
	(1.6436)	*(34.7589)*	*(42.1944)*	*(42.3986)*	*(104.3953)*
Adjusted R-Squared	0.1100	0.2379	0.2432	0.2441	0.2589
Akaike Inf. Crit.	976.4946	968.6586	971.8511	973.7097	977.4416
Note:	**p<0.05; **p<0.01; ***p<0.001*				

Standard errors are shown in parentheses and italics. Statistically significant associations are shown in red. The adjusted R-squared statistic show how much of the variance is explained, but should be interpreted with caution given that the addition of any predictor, regardless of its importance, will increase this statistic. The Akaike's Information Criterion (AIC) assesses comparative model fit and also penalizes overfitting by minimizing information loss. Both should be considered when interpreting model fit.

Table A5. Prison Population and COVID-19 Case Fatality Rate					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Prison Population	0.00001	0.00004	0.00004	0.00004	0.00004
	(0.0001)	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.0001)*
Population Density		0.00002	-0.00001	-0.0007	-0.0006
		(0.0002)	*(0.0002)*	*(0.0004)*	*(0.0004)*
Proportion 65+		4.3023	4.0116	4.3730	3.6795
		(2.8197)	*(2.8526)*	*(2.8292)*	*(3.1908)*
Proportion Non-Hispanic White		-0.1994	-0.5724	-0.6282	-0.7436
		(1.4449)	*(1.5201)*	*(1.5042)*	*(1.5184)*
Proportion Disabled		-1.3644	-0.1537	-0.7068	-1.6504
		(1.9672)	*(2.6412)*	*(2.6308)*	*(2.9338)*
Average Household Size		-0.7476	-0.9011	-0.8131	-1.0154
		(0.5118)	*(0.5391)*	*(0.5356)*	*(0.5878)*
Proportion Poor			-0.3748	-1.4713	-2.9686
			(2.0950)	*(2.1590)*	*(2.4181)*
Proportion Service Workers			-2.9643	-2.4199	-2.2145
			(3.1710)	*(3.1516)*	*(3.3512)*
Proportion Public Transit				23.7628	22.1515
				(13.0940)	*(13.2289)*
Proportion Uninsured					2.9368
					(2.5312)
Life Expectancy					-0.0304
					(0.0582)
Diabetes Prevalence					0.0152
					(0.0638)
Constant	**1.4703***	2.9190	4.0765	3.9289	6.8483
	(0.0817)	*(1.8062)*	*(2.1906)*	*(2.1688)*	*(5.3366)*
Adjusted R-Squared	0.0001	0.0648	0.0731	0.1012	0.1200
Akaike Inf. Crit.	286.2011	288.5026	291.4848	289.9331	293.5132
Note:	**p<0.05; **p<0.01; ***p<0.001*				

Standard errors are shown in parentheses and italics. Statistically significant associations are shown in red. The adjusted R-squared statistic show how much of the variance is explained, but should be interpreted with caution given that the addition of any predictor, regardless of its importance, will increase this statistic. The Akaike's Information Criterion (AIC) assesses comparative model fit and also penalizes overfitting by minimizing information loss. Both should be considered when interpreting model fit.

Table A6. Prison Population and COVID-19 Crude Mortality Rate					
	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Prison Population	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0001)	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.0001)*
Population Density		-0.0001	-0.0001	**-0.0006***	**-0.0006***
		(0.0001)	*(0.0001)*	*(0.0003)*	*(0.0003)*
Proportion 65+		2.3534	2.2908	2.5730	1.9401
		(1.9696)	*(1.9950)*	*(1.9711)*	*(2.2347)*
Proportion Non-Hispanic White		-1.2255	-1.2806	-1.3242	-1.3412
		(1.0093)	*(1.0631)*	*(1.0479)*	*(1.0634)*
Proportion Disabled		-1.6105	-1.6286	-2.0604	-2.5727
		(1.3741)	*(1.8472)*	*(1.8328)*	*(2.0547)*
Average Household Size		-0.4639	-0.5131	-0.4444	-0.5206
		(0.3575)	*(0.3770)*	*(0.3731)*	*(0.4116)*
Proportion Poor			0.7082	-0.1478	-0.8612
			(1.4652)	*(1.5041)*	*(1.6935)*
Proportion Service Workers			-1.5736	-1.1486	-0.8354
			(2.2177)	*(2.1956)*	*(2.3470)*
Proportion Public Transit				**18.5501***	18.0594
				(9.1223)	*(9.2648)*
Proportion Uninsured					1.4020
					(1.7727)
Life Expectancy					-0.0081
					(0.0408)
Diabetes Prevalence					0.0240
					(0.0447)
Constant	**0.9284*****	**3.0411***	**3.3956***	**3.2804***	3.9143
	(0.0565)	*(1.2617)*	*(1.5321)*	*(1.5110)*	*(3.7375)*
Adjusted R-Squared	0.0152	0.0603	0.0664	0.1017	0.1111
Akaike Inf. Crit.	201.3787	205.9829	209.2451	206.8031	211.5932
Note:	**p<0.05; **p<0.01; ***p<0.001*				

Standard errors are shown in parentheses and italics. Statistically significant associations are shown in red. The adjusted R-squared statistic show how much of the variance is explained, but should be interpreted with caution given that the addition of any predictor, regardless of its importance, will increase this statistic. The Akaike's Information Criterion (AIC) assesses comparative model fit and also penalizes overfitting by minimizing information loss. Both should be considered when interpreting model fit.

Table A7. Incarceration Density and COVID-19 Infection Rate					
	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Incarceration Density	**3.6041***	**2.6634**	**2.7276**	**2.7168**	**2.7589**
	(0.9367)	*(0.9239)*	*(0.9353)*	*(0.9400)*	*(0.9440)*
Population Density		**-0.0082***	**-0.0076***	-0.0098	-0.0104
		(0.0035)	*(0.0036)*	*(0.0080)*	*(0.0080)*
Proportion 65+		-79.4499	-73.9346	-72.7874	-83.6467
		(53.7547)	*(54.4337)*	*(54.7949)*	*(61.7284)*
Proportion Non-Hispanic White		**-56.3148***	-48.5376	-48.7372	-44.3796
		(27.7541)	*(29.2180)*	*(29.3507)*	*(29.6248)*
Proportion Disabled		-51.0453	-82.6477	-84.4603	-77.4627
		(37.7403)	*(50.7071)*	*(51.2651)*	*(57.1514)*
Average Household Size		-9.5582	-7.2380	-6.9557	-2.5230
		(9.8117)	*(10.3508)*	*(10.4357)*	*(11.4508)*
Proportion Poor			33.2833	29.6335	50.4603
			(40.2808)	*(42.1592)*	*(47.1918)*
Proportion Service Workers			23.3196	25.1290	36.6296
			(60.7858)	*(61.3300)*	*(65.1711)*
Proportion Public Transit				78.4948	119.1429
				(255.2641)	*(257.7992)*
Proportion Uninsured					-41.4420
					(49.3040)
Life Expectancy					0.8025
					(1.1346)
Diabetes Prevalence					0.9817
					(1.2432)
Constant	**63.0833***	**163.7037***	**145.7193***	**145.2781***	56.1666
	(1.6190)	*(34.7087)*	*(42.1932)*	*(42.3988)*	*(104.1968)*
Adjusted R-Squared	0.1158	0.2421	0.2484	0.2491	0.2651
Akaike Inf. Crit.	975.7407	968.0171	971.0540	972.9505	976.4725
Note:	**p<0.05; **p<0.01; ***p<0.001*				

Standard errors are shown in parentheses and italics. Statistically significant associations are shown in red. The adjusted R-squared statistic show how much of the variance is explained, but should be interpreted with caution given that the addition of any predictor, regardless of its importance, will increase this statistic. The Akaike's Information Criterion (AIC) assesses comparative model fit and also penalizes overfitting by minimizing information loss. Both should be considered when interpreting model fit.

Table A8. Incarceration Density and COVID-19 Case Fatality Rate					
	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Incarceration Density	0.0111	0.0233	0.0246	0.0213	0.0195
	(0.0467)	*(0.0481)*	*(0.0487)*	*(0.0482)*	*(0.0484)*
Population Density		0.00002	-0.000003	-0.0007	-0.0006
		(0.0002)	*(0.0002)*	*(0.0004)*	*(0.0004)*
Proportion 65+		4.3305	4.0271	4.3727	3.6659
		(2.7999)	*(2.8347)*	*(2.8115)*	*(3.1682)*
Proportion Non-Hispanic White		-0.1774	-0.5435	-0.6036	-0.7197
		(1.4456)	*(1.5216)*	*(1.5060)*	*(1.5205)*
Proportion Disabled		-1.3539	-0.1698	-0.7158	-1.6560
		(1.9657)	*(2.6406)*	*(2.6304)*	*(2.9333)*
Average Household Size		-0.7396	-0.8935	-0.8084	-1.0108
		(0.5111)	*(0.5390)*	*(0.5355)*	*(0.5877)*
Proportion Poor			-0.3399	-1.4394	-2.9388
			(2.0977)	*(2.1632)*	*(2.4221)*
Proportion Service Workers			-2.9540	-2.4090	-2.1941
			(3.1655)	*(3.1468)*	*(3.3449)*
Proportion Public Transit				23.6459	22.0588
				(13.0975)	*(13.2314)*
Proportion Uninsured					2.9386
					(2.5305)
Life Expectancy					-0.0299
					(0.0582)
Diabetes Prevalence					0.0158
					(0.0638)
Constant	**1.4668***	2.8697	4.0222	3.8893	6.7677
	(0.0807)	*(1.8078)*	*(2.1973)*	*(2.1755)*	*(5.3479)*
Adjusted R-Squared	0.0005	0.0657	0.0738	0.1017	0.1203
Akaike Inf. Crit.	286.1510	288.3993	291.3944	289.8789	293.4677
Note:	**p<0.05; **p<0.01; ***p<0.001*				

Standard errors are shown in parentheses and italics. Statistically significant associations are shown in red. The adjusted R-squared statistic show how much of the variance is explained, but should be interpreted with caution given that the addition of any predictor, regardless of its importance, will increase this statistic. The Akaike's Information Criterion (AIC) assesses comparative model fit and also penalizes overfitting by minimizing information loss. Both should be considered when interpreting model fit.

Table A9. Incarceration Density and COVID-19 Crude Mortality Rate

	Model 1	Model 2	Model 3	Model 4	Model 5
	Bivariate	*Demographics*	*Economics*	*Commuting*	*Health*
Incarceration Density	0.0489	0.0463	0.0493	0.0468	0.0462
	(0.0322)	*(0.0336)*	*(0.0340)*	*(0.0336)*	*(0.0339)*
Population Density		-0.0001	-0.0001	**-0.0006***	**-0.0006***
		(0.0001)	*(0.0001)*	*(0.0003)*	*(0.0003)*
Proportion 65+		2.3315	2.2699	2.5374	1.8767
		(1.9532)	*(1.9797)*	*(1.9565)*	*(2.2161)*
Proportion Non-Hispanic White		-1.1857	-1.2258	-1.2724	-1.2865
		(1.0085)	*(1.0626)*	*(1.0480)*	*(1.0635)*
Proportion Disabled		-1.5834	-1.6514	-2.0742	-2.5815
		(1.3713)	*(1.8442)*	*(1.8305)*	*(2.0517)*
Average Household Size		-0.4585	-0.5044	-0.4385	-0.5136
		(0.3565)	*(0.3764)*	*(0.3726)*	*(0.4111)*
Proportion Poor			0.7620	-0.0893	-0.8017
			(1.4650)	*(1.5053)*	*(1.6942)*
Proportion Service Workers			-1.5328	-1.1107	-0.7741
			(2.2107)	*(2.1898)*	*(2.3397)*
Proportion Public Transit				**18.3086***	17.8516
				(9.1144)	*(9.2550)*
Proportion Uninsured					1.4088
					(1.7700)
Life Expectancy					-0.0070
					(0.0407)
Diabetes Prevalence					0.0254
					(0.0446)
Constant	**0.9279*****	**2.9908***	**3.3163***	**3.2134***	3.7399
	(0.0557)	*(1.2611)*	*(1.5345)*	*(1.5139)*	*(3.7407)*
Adjusted R-Squared	0.0199	0.0637	0.0698	0.1042	0.1137
Akaike Inf. Crit.	200.8240	205.5748	208.8243	206.4877	211.2597
Note:					**p<0.05; **p<0.01; ***p<0.001*

Standard errors are shown in parentheses and italics. Statistically significant associations are shown in red. The adjusted R-squared statistic show how much of the variance is explained, but should be interpreted with caution given that the addition of any predictor, regardless of its importance, will increase this statistic. The Akaike's Information Criterion (AIC) assesses comparative model fit and also penalizes overfitting by minimizing information loss. Both should be considered when interpreting model fit.

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