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The Influence of Political Party Affiliation and Park Accessibility on COVID-19 case incidence

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Abstract

This paper examines the joint effect of political party affiliation and the urban landscape, as measured by access to parks, on case rates during the COVID-19 pandemic in the United States. The 2016 and 2020 U.S. Presidential Election returns are used as a proxy for a county's political party affiliation prior to and during the COVID-19 pandemic. A county population's spatial relationship to its parks encapsulates the green open space within an urban environment. The data set controls for features of the built environment, socioeconomic and demographic characteristics (race, gender, income, education), COVID-19 government regulations, and presidential election returns. Using an OLS model, I estimate how political party affiliation in the 2016 election and access to parks affect COVID-19 case rates. I conclude that Democratic counties are associated with increased case rates. I identify that greater park access in Republican counties is correlated with increased case rates. Using a regression discontinuity, I conclude that as 2020 Republican counties lean Democratic, case rates fall. While Democratic counties are correlated with lower case rates, as they lean heavily Democratic case rates rise. Greater park access is correlated with a slight increase in case rates prior to the 2020 election. The paper recommends that future research should define political party affiliation and the urban landscape at a more granular level and use pooled cross section or panel data.

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1. Introduction

The COVID-19 pandemic is creating some of the most severe health, economic and social consequences of the 21st century. The pandemic's lasting effects challenge the current global health system and future socioeconomic development (Wang *et al.,* 2021). As of October 2021, nearly 5 million individuals died from COVID-19 globally. The virus spreads through viral particles from person-to-person, meaning dense urban areas bear numerous infections.

This paper identifies how political and environmental county characteristics affect COVID-19 case incidence. Specifically, this paper utilizes a two-pronged approach to study the effects of both political party affiliation and the urban landscape on public health outcomes. I analyze the influence of political party affiliation on COVID-19 infection, while differentiating by the spatial relationship between citizens and parks. The COVID-19 pandemic couples with pre-existing sociopolitical divisions to frame the national political debate and further divide contemporary society. I hypothesize that Democratic counties engage in discourse which encourages more social distancing behaviors, implying that as counties lean Democratic, they exhibit lower case rates. Furthermore, I expect that parks correlate with lower case rates because they allow people to continue socially distanced recreational and social activities.

The contributions of this work advance the findings of case studies in Chicago, Illinois (Kashem *et al.,* 2021) and King County, Washington (Liu, Liu and Guan, 2021), which find that socioeconomic characteristics more greatly influence COVID-19 spread than other built environment characteristics, including density. The built environment is the man-made surroundings that create conditions for human activity, eventually influencing long-term health outcomes. I expand the scope of analysis with respect to both characteristics of the built environment and geographical scale. Anti-science rhetoric, stemming from President Trump's false claims about COVID-19, is divided along political party lines. Given this dynamic, I measure the influence of political party affiliation, alongside characteristics of the built environment (public green space, density, and transportation methods), while controlling for socioeconomic characteristics (age, race, income, and education), across every county in the United States.

Using an OLS regression, I determine that voting Democratic in the 2016 U.S. Presidential Election is associated with a statistically significant increase in case rates. Greater park access is correlated with higher case rates in Republican counties and lower case rates in Democratic counties; however, this effect is only statistically significant among Republican counties. Using a regression discontinuity design, I measure the divergence in case rates among moderate counties before and after the 2020 U.S. Presidential Election. Both before and after the 2020 election, as Republican counties lean more Democratic, case rates fall. This effect is statistically significant in the pre-election framework. While Democratic counties are correlated with lower case rates, as they lean heavily Democratic, case rates rise. These effects are statistically significant in the pre-election framework. Prior to the 2020 election, greater park access is associated with a statistically significant increase in case rates. However, after the election it is associated with a near zero and statistically insignificant effect.

The first section below provides a background to the existing literature. Next, I explain the sample selection and present an econometric model that can be used to generate specific hypotheses. Then, I present my results and provide a discussion of their interpretation. Finally, I offer concluding remarks for future research.

2. Literature

There is a growing body of literature on COVID-19 across different spatial-temporal contexts, but Peng (2020) says there is not enough findings on the influence of the built environment (Peng *et al.,* 2020). Studies examining the relationship between the built environment and public health reach contradictory findings, which Marshall, Piatkowski and Garrick (2014) attribute to numerous factors beyond specific built environment characteristics that also influence public health outcomes (Marshall, Piatowski and Garrick, 2014). Moreover, Frank and Wali (2021) attribute prior researchers' difficulty in drawing correlations between density and COVID-19 infection rates to unreliable data at the beginning of the pandemic (Frank and Wali, 2021). Additionally, Kang *et al.,* (2020) studies the spatial dynamics of the COVID-19 outbreak in mainland China; however, they include only six different neighborhood types, which could exclude certain relationships (Kang *et al.,* 2020).

Since the built environment constrains human movement, it affects infection risk (Wang *et al.,* 2021) through environmental exposure (Frank and Wali, 2021). It indirectly affects public health through socioeconomic factors, demographic characteristics, climatology parameters, and baseline health conditions (Wang *et al.,* 2021). Therefore, Liu, Liu and Guan (2021) say that it is too soon to determine whether a high population density correlates with a high incidence of COVID-19 cases (Liu, Liu and Guan, 2021).

Scholars reach mixed findings on the influence of density and COVID-19 outcomes. Khavarian-Garmsier *et al.,* (2021) finds that density itself is not a major contributor to COVID-19 morbidity or mortality rates (Khavarian-Garmsir *et al.,* 2021).

Moreover, Hamidi, Sabouri and Ewing (2020) find that density accounts for only 23% of the variation in virus rates within the New Orleans metropolitan area, which is composed of variously dense counties (Hamidi, Sabouri and Ewing, 2020). By contrast, Wang *et al.,* (2021) finds a positive correlation between virus transmission and commercial and infrastructure density levels (Wang *et al.,* 2021). Furthermore, Frank and Wali (2021) find that population density is positively correlated with COVID-19 incidence, illustrating that compact development, where people live close together, can potentially spread infectious disease (Frank and Wali, 2021). However, residents of high dense communities can make behavior changes to live safely during an outbreak (Khavarian-Garmsir *et al.,* 2021), such as remote work and social distancing, leading to different COVID-19 outcomes across comparably dense areas (Liu, Liu and Guan, 2021).

Studies examining the built environment's relationship to COVID-19 outcomes also establish differing findings. Case studies in Chicago (Kashem et al., 2021) and King County, Washington (Liu, Liu and Guan, 2021) find that socioeconomic factors influence COVID-19 spread more than other built environment features. Furthermore, Wang *et al.,* (2021) finds a negative correlation between COVID-19 risk and green space availability (Wang *et al.,* 2021). Additionally, Frank and Wali (2021) find that tree canopy coverage, which represents a greener urban environment, is correlated with lower COVID-19 mortality rates (Frank and Wali, 2021).

Further, human mobility is important for modeling the spatial spread of COVID-19 (Gross *et al.,* 2020). Prior to the COVID-19 pandemic, Meng *et al.* (2005) uses inter-city connections to study the spatial spread of infectious diseases (Meng *et al.,* 2005). More recently, population migration explains how COVID-19 spread from the Hubei province (Gross *et al.,* 2020) and from New York City to surrounding metropolitan areas (Hamidi, Sabouri and Ewing, 2020). Furthermore, human mobility affects more than just virus transmission: Wali and Frank (2021) find an association between active travel (walking, biking) and lower rates of hospitalizations and deaths from COVID-19 (Wali and Frank, 2021). To account for pre-existing human mobility patterns, I control for commute mechanisms - driving over 45 minutes, taking active transport, or using public transport - and the share of elementary schools located near highways.

In addition to community wide characteristics of the built environment, socioeconomic characteristics and political party affiliation influence people's attitudes and behaviors about COVID-19, ultimately influencing virus transmission. Prior research finds correlations between the urban built environment and public health outcomes at the individual level (Saarloos, Kim and Timmermans, 2009). Socioeconomic factors are strong predictors of COVID-19 incidence in lower-income European countries (Sannigrahi *et al.,* 2020) and Washington D.C. (Hu *et al.,* 2021). Moreover, two studies identify that demographic structure influences virus incidence more than density (Nguimkeu and Tadadjeu, 2021; Federgruen and Naha, 2021). Additionally, a case study of Huangzhou's urban areas finds that a community's commercial prosperity level has a positive effect on COVID-19 contagion (Li *et al.,* 2021). A Tehran case study finds that areas with lower employment, literacy and car-ownership levels are more vulnerable to COVID-19, while areas with a greater portion of college educated individuals, who can do remote work, are less vulnerable (Khavarian-Garmsir *et al.,* 2021). Similarly, a Chicago case study finds an intersectional effect of the built environment, class and race: specifically, household size, education, and Latinx population have a positive relationship with COVID-19 prevalence over time (Kashem *et al.,* 2021). Frank, Andersen and Schmid (2004) find an increased correlation between urban form and transportation-related activity patterns for White individuals over Black individuals (Frank, Andresen and Schmid, 2004), who are also more likely to be hospitalized and die from COVID-19 (Wali and Frank, 2021). To account for the influence of pertinent socioeconomic characteristics I control for gender, race, income, and education levels.

Socioeconomic characteristics are correlated with political party affiliation, but they are not an exact proxy. Leventhal *et al.,* (2021) identifies an association between political party affiliation and social distancing tendencies among 9^{th} grade students in California. They find that Republicans more commonly practice infrequent physical distancing, engage in more social recreational activities, and are more likely to attend an indoor event or host a party with more than 10 people (Leventhal *et al.,* 2021). Furthermore, Naeim *et al.,* (2021) finds that Republican-identifying individuals are less likely to wear a mask or be "very concerned" about COVID-19, and they are more likely to report a willingness to return to normal activities (Naeim *et al.,* 2021). To control for the influence of political party affiliation, I use returns from the 2016 U.S. Presidential Election to define the political leanings of the population prior to the onset of the pandemic. I use returns from the 2020 U.S. Presidential Election to study how social coherence influences COVID-19 outcomes among moderate counties.

3. Research Methods

A. Data

The purpose of this analysis is to determine how political party affiliation and public parks jointly affect COVID-19 cases in the United States. While many articles study the effect of various aspects of the built environment on COVID-19 infection rates, this paper expands the geographic scope of prior analyses by drawing upon data from every county in the United States.

The data have four segments: county characteristics, government mandates, political leanings, and COVID-19 outcomes. County characteristics include features of the urban landscape and demographics. These data are expressed as annual percentages, counts or averages from 2010 to 2020. I use the National Environmental Public Health Tracking Network to extract variables which describe the built environment, including both spatial relationships and commute patterns. I include the proportion of the population living within 0.5 miles of a park, the proportion of children aged 5-9 years old living within 0.5 miles of a public elementary school, and the proportion of elementary schools within 150m of a highway. I also include the proportion of workers over 16 years-old who drive over 45 minutes, take active transport (walking, bicycling), or use public transport to control for commute mechanisms. Using the 2020 U.S. Census, I measure the proportional breakdown of the population by gender (male, female) and race (White, Black, Asian, other). Using the U.S. Department of Agriculture Economic Research Service, I procure a county's 2019 median household income and educational attainment levels. I calculate a dummy variable denoting whether most of the county has some college level education. These variables provide a snapshot of the pre-pandemic world, so I do not differentiate the specific year between 2010 and 2020 that they are recorded in.

The data pertaining to government mandates represent COVID-19 regulations. The levels of observations are county-by-day from March 15, 2020 to August 15, 2021. There are six different county government orders, which I obtain from the Center for Disease Control. These data serve as important covariates of a county's political leaning and imposed COVID-19 regulatory policy. It is important to note that due to time constraints I am not able to procure data pertaining to state level stay-at-home orders.

I obtain raw voting counts from the 2016 and 2020 U.S. Presidential Election from the M.I.T. Election Lab. I calculate the percentage of the county that votes Democratic or Republican in 2016 and 2020. I exclude the percentage that votes "other" due to the two-party nature of the American political system. I classify counties as Democratic leaning in 2016 or 2020 if a greater proportion of the county votes Democratic than Republican in the respective presidential election. I use the 2016 dummy variable as a proxy indicating a county's political leanings prior to the COVID-19 pandemic, while the 2020 dummy variable represents a county's political leanings during the pandemic. I also calculate a dummy variable identifying whether a county's political leanings flip between the 2016 and the 2020 election.

For the final subsection, COVID-19 cases, the levels of observation are county-by-day from January 21, 2020 to August 15, 2021. However, I merge the data from March 15, 2020 onwards to align with the government mandated stay-at-home order data that I control for. Using the *New York Times* COVID-19 tracker, I procure the daily total confirmed cumulative cases by county, which I use to calculate the daily new cases. To smooth the data points and control for the fixed effects of county population and size, I calculate the seven-day moving averages of new cases per 100,000 people. Finally, to further normalize the data, I take the natural log of the seven-day moving average of cases per 100,000 people.

Given the fact that I extract these independent variables from multiple datasets across a variety of years from 2010 to 2020, there are disparities in identifying county or census-designated county equivalents. To satisfy equivalent observation counts for every independent variable, I exclude certain observations, resulting in a sample size reduction of 34 county or census-designated county equivalents.

Table 1 provides summary statistics for all counties, differentiating by their political party leaning in the 2016 U.S. Presidential Election. I also report the mean difference between Democratic and Republican leaning counties and the two-sample t-statistic for each variable.

Table 1: Summary Statistics - All Counties									
Variable	2016 Republican Counties				2016 Democratic Counties				Mean difference
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	(t-test)
COVID-19 case rate	2.51	1.32	-3.45	7.41	2.40	1.27	-4.39	6.71	0.10 (33.19)
*Living near park	0.26	0.23	0.01	0.89	0.36	0.26	0.01	0.93	-0.11 (-9.01)
*Living near elementary	0.61	0.19	0.01	0.94	0.62	0.17	0.01	0.96	-0.01 (-1.02)
*Schools near highway	0.29	0.49	0.01	1.69	0.41	0.5	0.01	1.7	-0.11 (-4.64)
*Driving 45+ minutes to work	8.89	5.63	0.01	18.28	9.24	5.67	0.03	18.29	-0.36 (-1.27)
*Taking active transport (walk, bike) to work	3.17	2.14	0.01	8.61	3.79	2.2	0.01	8.62	-0.62 (-5.88)
*Taking public transport to work	0.43	0.55	0.01	4.02	1.62	1.28	0.01	4.13	-1.19 (-33.62)
*Female	0.50	0.02	0.27	0.57	0.51	0.02	0.32	0.54	-0.01 (-6.72)
Median household income, 2019	54695.85	12351.73	28234	123697	60688.69	21898.85	24732	151806	-5992.84 (-8.50)
*Some college, 0/1	0.56	0.5	0	1	0.74	0.44	0	1	-0.18 (-7.48)
*White	0.88	0.12	0.21	0.99	0.67	0.23	0.08	0.99	0.20 (29.01)
*Black	0.07	0.1	0	0.52	0.22	0.24	0	0.87	-0.15 (-23.15)
*Asian	0.01	0.01	0	0.43	0.04	0.06	0	0.43	-0.03 (-24.20)
*Other race	0.04	0.06	0	0.75	0.06	0.11	0.01	0.89	-0.02 (-4.72)
Total population	56924.18	137673.8	169	4485414	365068.7	732410.2	404	10000000	-308144.5 (-19.75)
*Democratic, 2016	0.26	0.1	0.03	0.49	0.59	0.1	0.42	0.88	-0.32 (-67.44)
*Republican, 2016	0.68	0.1	0.36	0.96	0.35	0.09	0.08	0.49	0.33 (65.28)
*Political party change 2016 to 2020	0.01	0.11	0	1	0.31	0.46	0	1	-0.29 (-28.36)

Note: 2020 U.S. Census, National Environmental Public Health Tracking Network, and the Department of Agriculture Economic Research Service; Observations: 2,622 (2016 Republican Counties); 485 (2016 Democratic Counties); *denotes variables as proportions; COVID-19 case rate is the natural log of the seven-day moving average.

These summary statistics are helpful for drawing inferences about the compositions of Democratic and Republican leaning counties. There is a statistically significant difference in case rates given a county's 2016 political party affiliation: case rates are 10% lower in Democratic counties. This provides initial support for my hypothesis that attitudes in Democratic societies encourage behaviors translating to lower case incidence. The difference in park accessibility levels between Democratic and Republican counties is statistically significant, such that 11% more of the population in Democratic counties lives within 0.5 miles of a park. Democratic counties offer greater park access and report lower case rates, illustrating that access to space may offer beneficial public health outcomes. Furthermore, a larger, statistically significant share of the population in Democratic counties rely upon public transit. I expect that individuals are more likely to rely upon public transport systems when they are more robust, which generally exist in big cities. This illustrates a potential association between Democratic counties and urban areas with stronger public transport systems. The share of counties who flip their political party affiliation between the 2016 and 2020 election is 29% higher in counties that lean Democratic in the 2016 election, and this difference is statistically significant. It is important to note that this difference signifies a change in the majority vote share but does not measure the percentage change in vote share. Additionally, the percentage difference in 2019 median household incomes between Republican and Democratic counties is statistically significant, such that Democratic counties are associated with higher income levels. Including income as a covariate is important given that lower socioeconomic status communities are associated with worse access to health care and subsequently poorer health outcomes.

Due to data accessibility constraints, I do not overcome these issues: I use cross-sectional data and county-level features of the urban landscape, which do not provide causality between the built environment and public health outcomes.

B. Econometric Design

This paper uses two approaches to explore the intersection of political party affiliation and the built environment on public health outcomes. The 2016 and 2020 U.S. Presidential Election returns serve as a proxy for political party affiliation, while the spatial relationship between a county's population and its parks captures the open space within a built environment. The first framework measures the relationship between key features of the urban landscape, a county's pre-pandemic political leanings, and COVID-19 case rates. The second framework estimates how COVID-19 case rates differ for moderate counties that lean Democratic in the 2020 U.S. Presidential Election, while controlling for park accessibility levels.

The main dependent variable is the natural log of COVID-19 cases per 100,000 people. The main independent variables are a county's 2016 or 2020 political party affiliation and the percentage of the population that lives within 0.5 miles of a park. These independent variables capture how both a county's political viewpoint and urban landscape affect COVID-19 case rates. I perform heterogeneity analyses differentiating case rates by county political viewpoints and park accessibility levels. The previously mentioned county characteristics control for other important covariates of COVID-19 infection rates (man-made features of the community, transportation means, race, income, education, and COVID-19 regulatory policy). COVID-19 cases are not linear over time, so I construct a month-year dummy variable for each month within the 18-month observation period. I control for time on a monthly basis, instead of weekly, to minimize the influence of an extraneously large number of additional degrees of freedom.

C. Ordinary Least Squares Regression

I perform an ordinary least squares (OLS) regression, estimating the correlation between my main independent variables, a county's 2016 voting behavior and residents' spatial proximity to parks, and my outcome variable, COVID-19 case rates. I hypothesize that societal attitudes and space, measured through park accessibility, influence the spread of COVID-19. Specifically, I expect that 2016 Republican counties hold societal attitudes which do not encourage social distancing behaviors as much as counties that vote Democratic. I further predict that counties with robust park access offer citizens a greater ability to spread out and social distance. For this reason, I expect that counties that vote Democratic in 2016 with the highest park accessibility levels exhibit the lowest COVID-19 case rates. By contrast, I expect that Republican counties with minimal park access reflect the highest case rates. Due to the nature of OLS regressions, this framework includes omitted variable bias and only informs me about correlation, not causation. Nevertheless, I estimate this regression to obtain a baseline understanding of the relationship between pre-pandemic political leanings, access to open green space, and COVID-19 cases. This framework is represented as

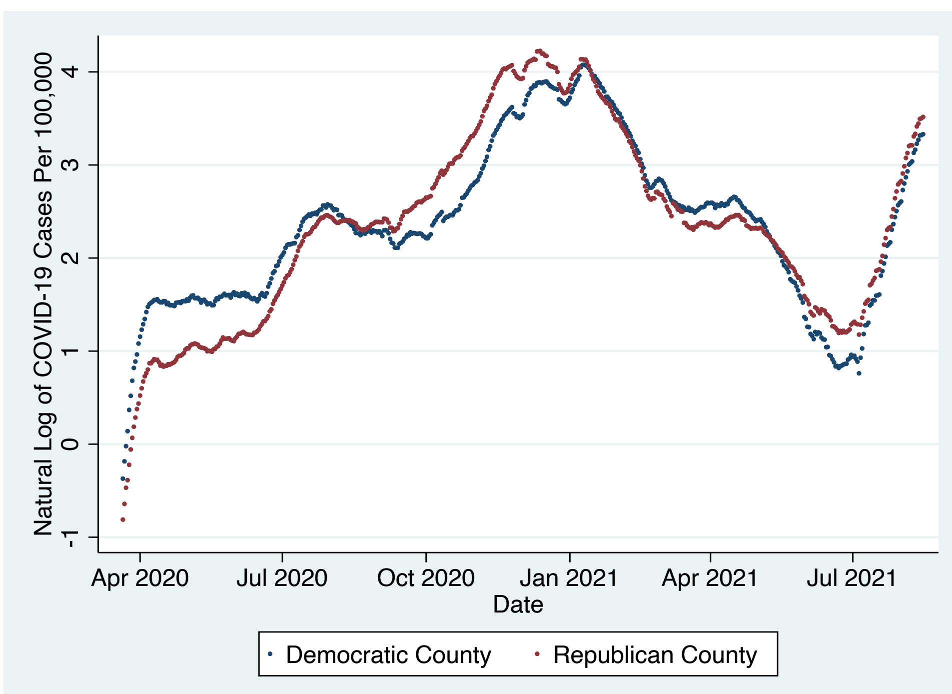
$$\textbf{(1)}\ ln\ (Y_{it}) = \beta_0 + \beta_1 DemLeaning16_i + \beta_2 Park_i + \beta_3 Park_i DemLeaning16_i + \sum_{t=1}^{17} \beta_t\, D_t + \boldsymbol{Z}_i'\boldsymbol{\Psi} + u_{it}$$

where $ln\ (Y_{it})$ represents the natural log of the normalized seven-day moving average of new COVID-19 cases per 100,000 people. Normalizing my outcome variable by population size ensures that my model controls for population density. $DemLeaning16_i$ is a dummy variable that classifies counties as Democratic leaning in 2016 if a greater proportion of the population votes Democratic than Republican in the 2016 election. Therefore, β_1 represents the difference in case levels between counties according to their pre-pandemic political affiliation. $Park_i$ is the percentage of the population living within 0.5 miles of a park, so β_2 captures the change in case levels given residential proximity to parks. $Park_i DemLeaning16_i$ is the interaction of a county's park access and pre-pandemic political party affiliatio, so β_3 encapsulates how a Democratic leaning county's case levels differ given greater access to parks. D_t is a dummy variable for each month-year, excluding D_{18} which corresponds to August 2021. Therefore, β_t captures the effect of time. $\boldsymbol{\Psi}$ is a vector of all coefficients for $\boldsymbol{Z}_i'$, a matrix of all the time invariant covariates (access to schools, transportation means, race, gender, education, total population, income, and COVID-19 regulatory policy). u_{it} captures the error.

The main coefficient of interest is β_3, which captures how case trends in a Democratic leaning county in 2016 differ given park accessibility. First, I examine how case incidence varies depending on a county's 2016 political classification (β_1) or its park accessibility (β_2).

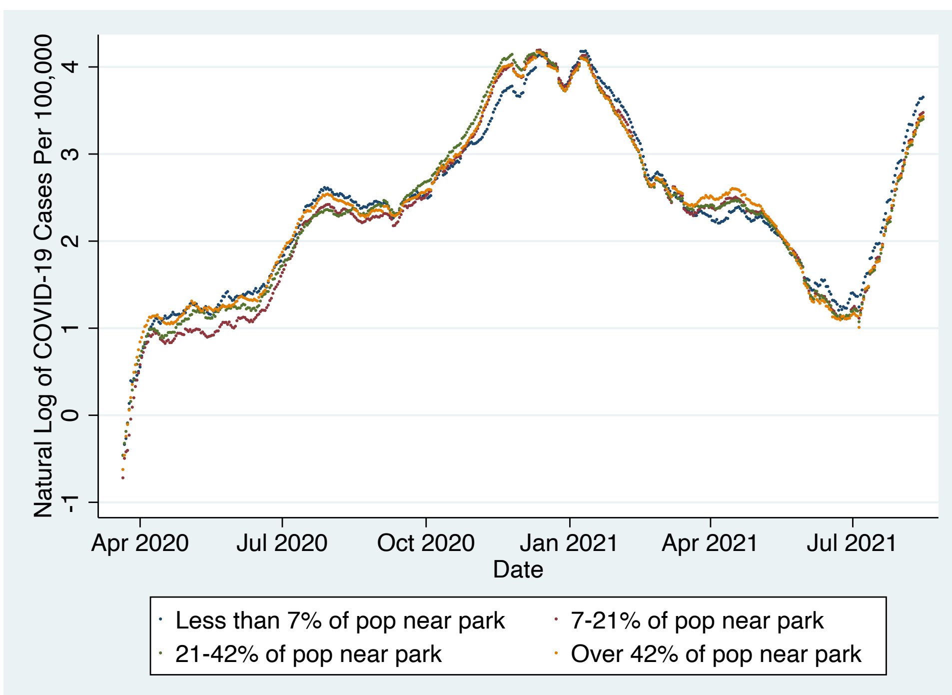
When differentiating COVID-19 case rates according to pre-pandemic political party affiliation, *Figure 1* shows that the disparity between new cases is larger when virus incidence in Republican counties is higher. Prior to September 2020, case rates rise more drastically in Democratic leaning counties. Then, case rates increase at much greater rates in Republican counties until February 2021. After this point, case rate trends in both county types mirror each other; this is also when vaccines become available to a large portion of American society. Trends in case rates fluctuate throughout the pandemic, indicating the importance of controlling for time within my model. Given the association between political party affiliation and the magnitude of the case differential, I hypothesize that β_1 is negative, implying that living in a Democratically leaning county is associated with lower levels of COVID-19 case rates in the community.

Figure 1. COVID-19 Case Rate by 2016 County Political Party Affiliation



By differentiating counties according to park accessibility quartiles, *Figure 2* shows that trends in case rates are generally comparable across all subsets of park access except during virus surges. During surges, cases spike most sharply for counties in the highest park accessibility quartile. While *Figure 2* provides an initial picture that case rates are relatively similar regardless of park access, I expect that after controlling for important socioeconomic and demographic covariates, my results will illustrate that parks lead to lower case rates. This is because corresponding park access allows people to safely continue their daily interpersonal activities by social distancing outside. This analysis insinuates that β_2 is positive and of small magnitude, meaning that case rates rise as a greater share of the county's population lives nearby parks.

Figure 2. COVID-19 Case Rate by Park Accessibility



I infer that access to parks and county political ideology are correlated along rural-urban lines: urban populations have greater access to robust publicly designated green space and are more Democratic leaning. Rural areas are inherently less industrialized and more dispersed than urban metros, meaning they require less officially designated parks. Therefore, access to parks does not wholly encapsulate the open green space within an urban landscape, illustrating one of its shortcomings as a measurement tool in this analysis. I proceed with this framework because of the stronger association of public parks, compared to expansive open green space, as a social and recreational meeting place. I hypothesize that urban populations are more likely to self-enforce social distancing given their Democratic political tendencies and greater ability to safely social distance while still interacting with others, through parks. Coupling this intuition with the interpretations of *Figure 1* and *Figure 2,* I extrapolate that β_3 is negative: Democratic counties with greater access to parks exhibit smaller changes in case rate levels throughout the pandemic.

D. Regression Discontinuity Design

Given the limitations of my OLS regression, I also estimate a regression discontinuity design to identify potential divergences in COVID-19 case rates among moderate counties that lean slightly Democratic or Republican in the 2020 election. Previously, I describe my expectations regarding the effect of societal attitudes and public spaces on COVID-19 case rates. President Biden encourages social distancing more than former President Trump. Therefore, those who vote for President Biden over former President Trump are more likely to share President Biden's concern surrounding COVID-19 transmission. I expect that as moderate counties lean Democratic in the 2020 election, they offer their citizens a greater public health benefit. However, the cutoff by which a county leans Democratic or not is arbitrarily placed at 50% of the total Democratic and

Republican votes (excluding "other"). For this reason, I estimate a pre- (2) and post-election (3) regression discontinuity design, such that

$$\textbf{(2)}\ ln\ (Y_{it}) = \beta_0 + \beta_1 Dem2020_i + \beta_2 DemLeaning20_i Dem2020_i + \beta_{RDD} DemLeaning20_i + \beta_3 Park_i + \sum_{t=1}^{8} \beta_t D_t + \boldsymbol{Z_i'\Psi_i} + \varepsilon_{it}$$

$$\textbf{(3)}\ ln\ (Y_{it}) = \beta_0 + \beta_1 Dem2020_i + \beta_2 DemLeaning20_i Dem2020_i + \beta_{RDD} DemLeaning20_i + \beta_3 Park_i + \sum_{t=9}^{17} \beta_t D_t + \boldsymbol{Z_i'\Psi_i} + \varepsilon_{it}$$

where $ln\ (Y_{it})$ represents the natural log of the normalized seven-day moving average of new COVID-19 cases per 100,000 people in county *i* on day *t*. β_1 captures the change in case rate levels given my running variable, $Dem2020_i$, which describes the proportion of the population in county *i* that votes for President Biden in the 2020 election. $DemLeaning20_i$ is a dummy variable classifying counties as Democratic if a greater portion of the county votes for President Biden than former President Trump in the 2020 election. Therefore, β_2 measures the change in case rates depending on $Liberal20_i Dem2020_i$, the interaction of the proportion of the population that votes for President Biden and achieves the 2020 Democratic leaning classification. β_{RDD} is the change in case rates at the 50% cutoff, thereby providing evidence as to how COVID-19 cases diverge in moderate counties. $Park_i$ is the proportion of the county population within 0.5 miles of a park, so β_3 captures the change in case levels given residents' spatial proximity to parks. D_t is a dummy variable for each month-year, such that β_t captures the effect of time. The pre-election framework includes data from March 15, 2020 to November 3, 2020; therefore, I include D_1 to D_8, excluding $D_{9.}$ The post-election framework estimates case rates from November 4, 2020 to August 15, 2021, so I include

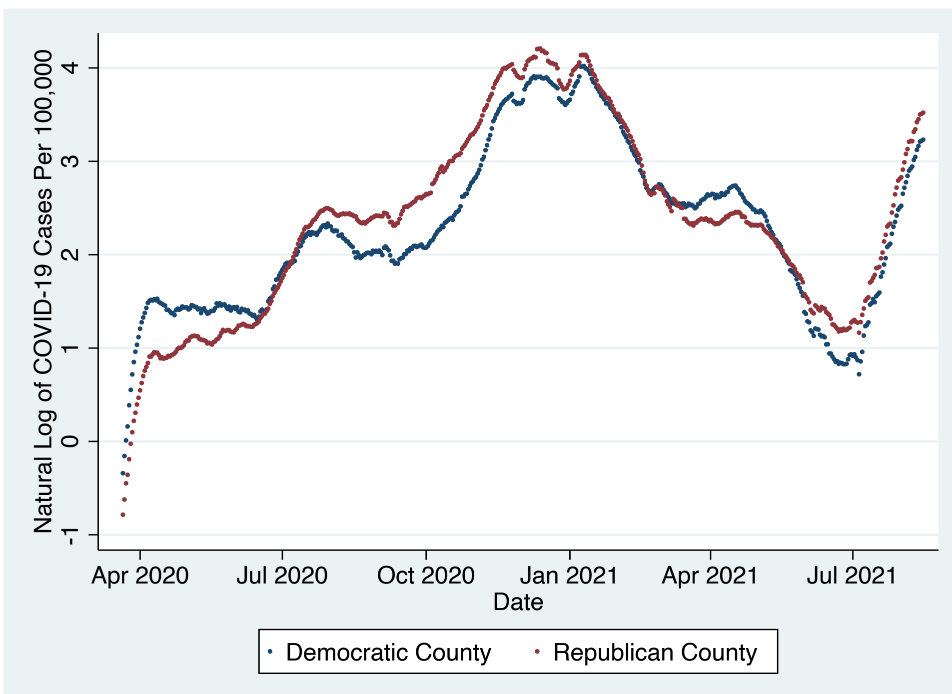
D_9 to D_{17}, excluding D_{18}. $\boldsymbol{Z_i'}$ is a vector of all coefficients for $\boldsymbol{\Psi_{it}}$, a matrix of all the time invariant covariates (access to schools, transportation means, race, gender, education, total population, income, and COVID-19 regulatory policy). ε_{it} captures the error.

By dividing the pandemic era in two periods in accordance with the 2020 election, I use a pre-post analysis to examine the interaction of the date being before or after President Biden's election. Applying a regression discontinuity analysis grants the ability to analyze how leaning slightly Democratic influences COVID-19 case rates in moderate counties that are similar in all aspects except a slight discrepancy in their 2020 vote shares. The more counties lean decisively Democratic or Republican, the less similar they are. For this reason, I restrict my analysis to a bandwidth of 10% on either side of a 50% Democratic vote share threshold within a county, thereby limiting the observation scale to counties where between 40% to 60% of the population votes Democratic in the 2020 election.

The main coefficient of interest is β_{RDD}, capturing the treatment effect (Democratic leaning), but I first examine how case incidence varies depending on the proportion of the county that votes for President Biden (β_1), a Democratic classification (β_2), and county park access (β_3).

There is a statistically significant difference in the amount of 2016 Republican or Democratic counties that change their political party affiliation in the 2020 election. For this reason, I include *Figure 3,* which differentiates case rates by a county's 2020 political leanings. Similar to the findings of *Figure 1,* COVID-19 case disparities are greater during surges where case rates in Republican counties surpass Democratic counties. The similarity between *Figure 1* and *Figure 3* illustrates that political party affiliation changes might not significantly affect overall trends in case rates. This highlights the importance of applying a regression discontinuity design to examine differences in cases at the threshold value of a county leaning Democratic or not in the 2020 election. Republican counties portray sharper increases in case rates, so I hypothesize β_1 is negative, such that as the share of the county population voting Democratic increases, case rates fall. Given the sharper increase in new cases in 2020 Republican affiliated counties during the first portion of the pandemic, I hypothesize that the magnitude of β_1 is greater in the pre-election model.

Figure 3. COVID-19 Case Rate by 2020 County Political Party Affiliation



β_2 captures case level differences as Democratically classified counties lean decisively more Democratic. Using political party affiliation as a proxy for societal attitudes surrounding personal and community wide COVID-19 risk, I hypothesize that Democratic individuals are more inclined to self-enforce social distancing behaviors.

Therefore, I expect that β_2 is negative, representing an association between predominately Democratic societies and lower COVID-19 levels. I expect that the magnitude of β_2 is larger in the post-election model, due to a high initial virus surge in high dense urban cities which tend to vote Democratic.

β_3 measures how COVID-19 case rates vary across counties with different park accessibility levels. I expect that parks promote self-enforced social distancing by offering a place to safely continue interpersonal activities. For this reason, I expect that β_3 is negative, depicting a benefit to living in an open and greener community. I define park access prior to the onset of the pandemic so I do not expect to see a large difference in β_3 levels between the pre- and post-election models. As mentioned previously, one shortcoming is that access to parks does not wholly capture the open space within a county, as it only measures publicly designated parks, not all expansive open green spaces.

Furthermore, I use the findings in *Figure 3* to inform my hypothesis about β_{RDD}, which measures the difference in case rates across moderate counties that lean Democratic. I hypothesize a correlation between leaning Democratic and lower case rates. Using political party affiliation as a proxy to model societal attitudes about COVID-19 within a county, I expect that not many moderate counties' attitudes change drastically from the onset of the pandemic. For this reason, I expect this effect to be comparable between the pre- and post-election models.

4. Results

A. Ordinary Least Squares Regression

Table 2 outlines the main results from the OLS regression **(1)** which estimates how political party affiliation and the urban landscape jointly affect COVID-19 case rates. See *Appendix Table A1* for month-year dummy variable estimates.

Table 2: OLS Regression, Natural Log of COVID-19 Cases	
	All counties
	Coefficient (Standard Error)
Democratic leaning, 0/1	0.06** (0.03)
*Living near park	0.06*** (0.02)
Interaction of Democratic leaning classification and proportion living near park	-0.01 (0.06)
*Living near elementary	0.35*** (0.03)
*Schools near highway	-0.04*** (0.01)
*Driving 45+ minutes to work	0.00*** (0.00)
*Taking active transport (walk, bike) to work	-0.02*** (0.00)
*Taking public transport to work	0 (0.01)
*Female	-0.39* (0.24)
Median household income, 2019	0.00 (0.00)
*White	-0.48*** (0.08)
*Black	0.59*** (0.08)
*Asian	-1.27*** (0.25)
*Some college, 0/1	-0.00 (0.01)
Population	0.00*** (0.00)
*Democratic vote share, 2016	0.33 (0.20)
*Republican vote share, 2016	1.13*** (0.19)
Constant	2.74*** (0.22)
Sigma_u	0.27
Sigma_e	0.89
Rho	0.09
Observations	1,396,630
Number of counties	3,102

Note: variable * denotes variables as proportions; ***p<0.01, **p<0.05, *p<0.1

Counties that vote Democratic in the 2016 election are associated with a 0.06% increase in case rates per 100,000. This effect is statistically significant at the 5% significance level. Previously, I associate Democratic counties with urban areas. These findings insinuate that after controlling for population density and other important covariates (transportation means, race, gender, income, education, COVID-19 regulatory policy, etc) case rates are only marginally higher in urban areas. This supports prior theories that high dense urban regions do not necessarily equate to more COVID-19 infections.

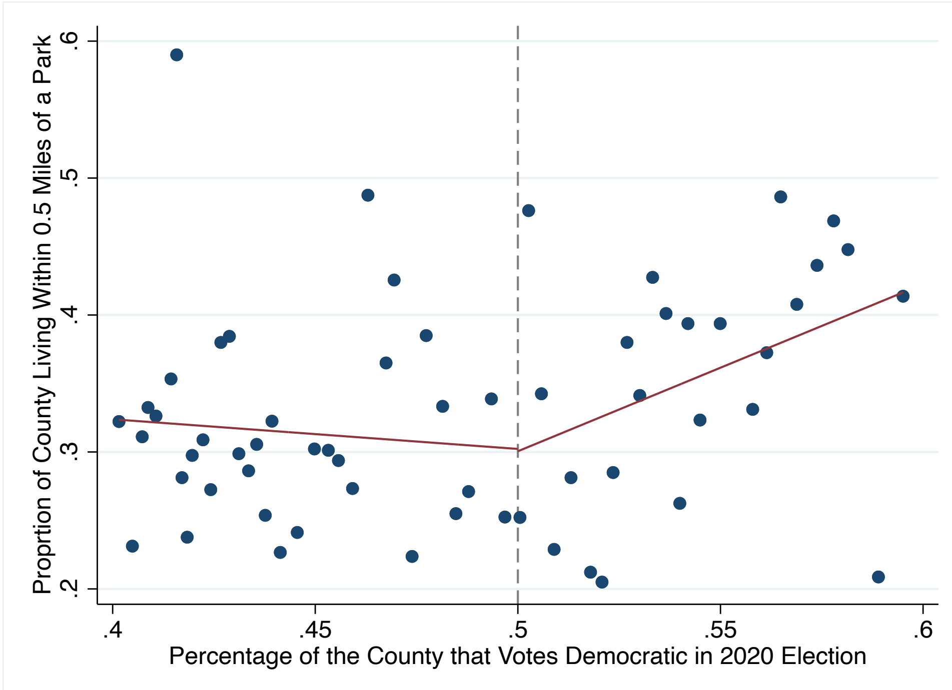
In 2016 Republican counties, as the proportion of the county that lives near a park increases by 1% then case rate rises by 0.06% per 100,000. This effect is statistically significant at the 1% significance level. This contradicts my original hypothesis that parks promote self-enforced social distancing by offering a place to safely continue regular interpersonal activities. These findings illustrate that individuals may overestimate the safety of outdoor socializing, such that the perceived safety level of socializing outside at parks does not significantly reduce virus transmission.

The interaction term highlights how case rate trends differ for 2016 Democratic voting counties as access to parks increase. If the proportion of citizens living near a park in a Democratic county increases by 1%, then case rates fall by 0.01% per 100,000. The near zero magnitude contradicts my hypothesis that an individual is better off living in a county that is Democratic with robust park access. However, this effect is not statistically significant.

B. Regression Discontinuity: Graphical Analysis

First, I present the graphical analysis to my regression discontinuity design. I plot the main built environment covariate, the proportion of the county population living within 0.5 miles of a park, according to my running variable, the proportion of a county that votes Democratic in the 2020 election. The key identifying assumption to any regression discontinuity design states that there is no change in any observable characteristics at the threshold value, such that $E(Y_{0i}|Dem2020_i)$ and $E(Y_{1i}|Dem2020_i)$ are continuous at $Dem2020_i$ and $Dem2020_i^* = 0.5$. This assumes that the only discontinuous jump in the data is due to my running variable, $Dem2020_i$, and that there are no other discontinuous jumps in other observable characteristics. The slope of the trendline in *Figure 4* models access to parks by 2020 voting behavior. It changes sign at the 50% Democratic vote share threshold, but there is no discrepancy in park access around this cutoff, providing initial confirmatory evidence for the key identifying assumption. Furthermore, *Figure 4* illustrates that as counties lean decisively more Democratic, their access to parks drastically increases, providing initial evidence that relates political party affiliation and features of the urban landscape: Democratic counties offer greater park access.

Figure 4. Park Accessibility Given 2020 Voting Patterns



See *Appendix Figure A1* to *Appendix Figure A12* for further evidence that no discontinuous jumps occur for other important covariates. After satisfying the key identifying assumption, I plot the outcome, the natural log of the seven-day moving average of new COVID-19 cases per 100,000 people, by the running variable, percentage of the county population that votes for President Biden in the 2020 election. I present this graph for both the pre- and post-election models, such that each includes data only before or after November 3, 2020.

Figure 5 demonstrates that prior to the 2020 election, there is a discrepancy between the natural log of the normalized new COVID-19 cases per 100,000 people around the threshold of a 50% Democratic vote share. Interestingly, at the 50% cutoff of leaning Democratic or not, counties that lean slightly Republican exhibit lower rates of new

COVID-19 cases during the first seven months of the pandemic. This means that among moderate counties, COVID-19 case incidence is higher in those that are slightly Democratic. This contradicts my original hypothesis that Democratic party affiliation is directly correlated with perceived risk attitudes and thus lower virus levels. However, I expect that after controlling for other important covariates I will see that as counties lean decisively more Democratic they are associated with a lower incidence of COVID-19 case rates.

Figure 5. COVID-19 Case Rate by 2020 Voting Patterns

Pre-Election: March 15, 2020 to November 3, 2020

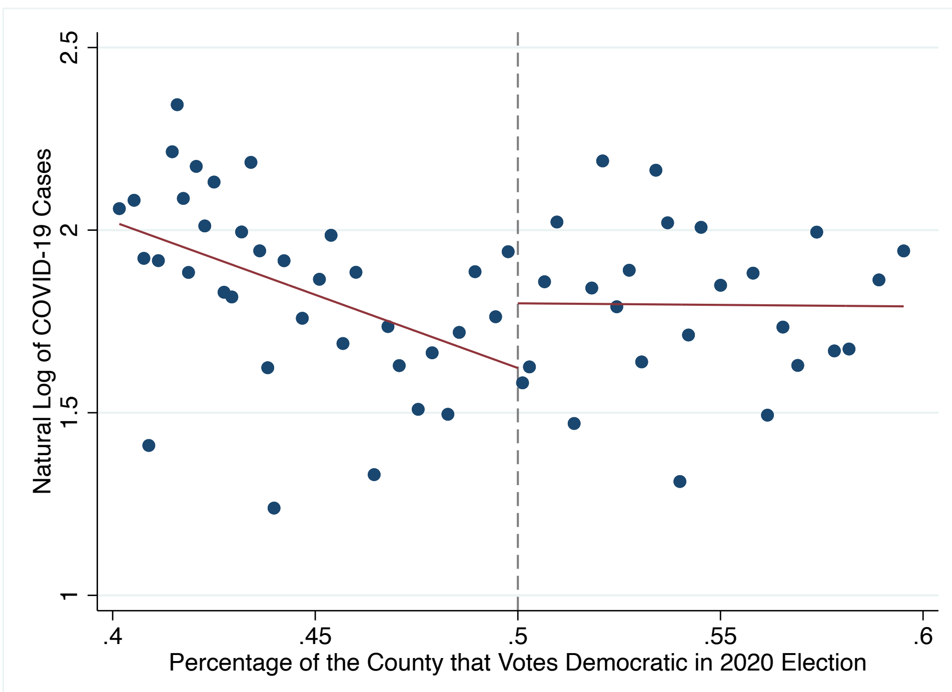
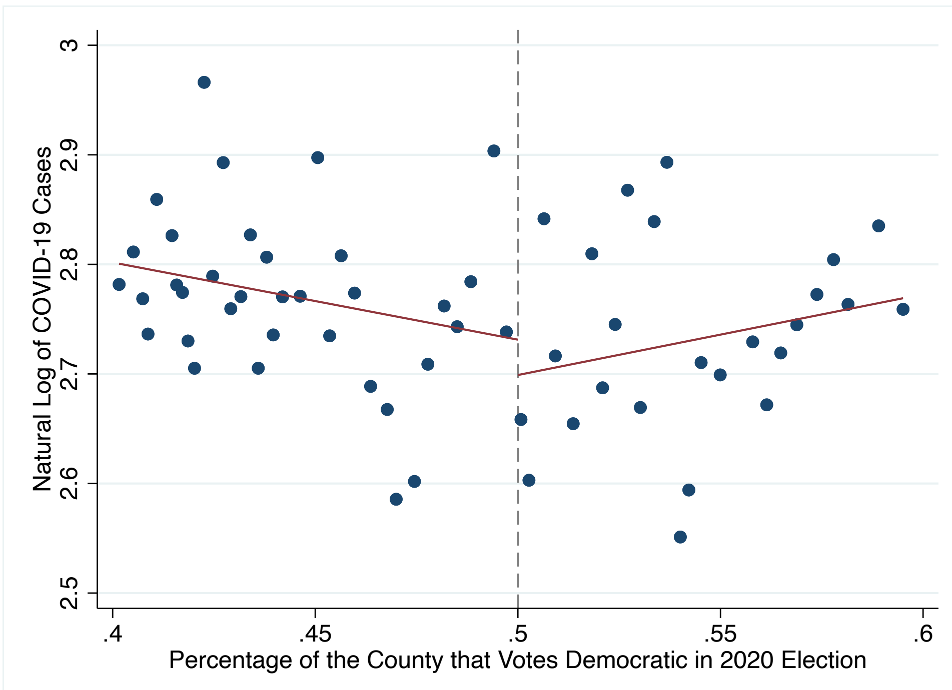


Figure 6 similarly illustrates a discrepancy in case levels around the 50% Democratic vote share threshold, although the magnitude differential is smaller than in the pre-election framework. After the 2020 election, counties that lean slightly Republican

exhibit higher case rates than counties that lean slightly Democratic. The direction of the discrepancy in the post-election model is opposite to that of the pre-election model but aligns with my hypothesis regarding the relationship between Democratic counties and lower case rates.

Figure 6. COVID-19 Case Rate by 2020 Voting Patterns

Post-Election: November 4, 2020 to August 15, 2021



Both *Figure 5* and *Figure 6* insinuate a discrepancy in COVID-19 case rates at the 50% Democratic vote share threshold, corroborating the necessity of using a regression discontinuity design to accurately capture the relationship between political party affiliation and public health outcomes. Prior to the 2020 election, Republican counties exhibit lower case rates than their Democratic counterparts (*Figure 5*); this effect reverses after the election (*Figure 6*). This result insinuates that the election of a president who encourages increased social distancing behavior does not necessarily influence COVID-19 attitudes. Further, it does not make people more inclined to practice social distancing if the county's political party affiliation does not align with their national leader. β_{RDD} captures the change in case rates across counties that are comparable in all aspects except whether they lean slightly Republican or slightly Democratic. In the pre-election model, I expect that β_{RDD} is positive: as a greater portion of the county votes for President Biden increases, case rates increase. In the post-election model, I expect that β_{RDD} is negative: as a county leans Democratic, case rates fall. This graphical analysis provides a more nuanced picture that political party affiliation does not directly correlate with virus levels, highlighting the importance of controlling for other factors beyond societal attitudes.

C. Regression Discontinuity: Regression Analysis

Table 3 outlines the main results from the regression discontinuity design estimating how COVID-19 case rates diverge around the 50% threshold of leaning Democratic in the 2020 election, differentiating by the pre- and post-election models. See *Appendix Table A2* and *Appendix Table A3* for month-year dummy variable estimates.

Table 3: Regression Discontinuity Design, COVID-19 Cases		
	(**2**) Pre-Election	(3) Post-Election
	Coefficient (robust standard error)	Coefficient (robust standard error)
*Democratic vote share, 2020	-6.38*** (1.25)	-0.95 (0.60)
Interaction of Democratic leaning classification and Democratic vote share, 2020	3.68** (1.61)	1.13 (0.85)
t-test between the proportion voting democratic in Republican vs. Democratic counties	*-2.69** (1.32)*	*0.18 (0.81)*
Democratic leaning 2020, 0/1	-1.79** (0.81)	-0.60 (0.43)
*Living near park	0.32*** (0.11)	0.00 (0.06)
*Living near elementary	1.67*** (0.24)	0.56*** (0.13)
*Schools near highway	-0.10** (0.04)	-0.01 (0.02)
*Driving 45+ minutes to work	0.02*** (0.00)	0.00 (0.00)
*Taking active transport (walk, bike) to work	-0.06*** (0.01)	-0.03*** (0.01)
*Taking public transport to work	-0.02 (0.03)	0.03* (0.02)
*Female	-0.85 (1.36)	-0.65 (0.96)
Median household income, 2019	0.00*** (0)	0.00 (0.00)
*White	-2.31*** (0.25)	-0.10 (0.12)
*Black	0.48* (0.26)	0.24 (0.15)
*Asian	-2.83*** (0.73)	-0.54 (0.72)
*Some college, 0/1	-0.11 (0.09)	0.00 (0.04)
Population	0.00** (0)	0.00 (0.00)
*Democrat vote share, 2016	3.56*** (0.69)	0.17 (0.35)
Constant	5.38 (0.83)	3.45*** (0.55)
Sigma_u	0.49	0.25
Sigma_e	0.91	0.74
Rho	0.22	0.10
Observations	102,410	139,702
Number of counties	501	501

Note: variable * denotes variables as proportions; ***p<0.01, **p<0.05, *p<0.1

As the proportion of the population in a Republican county that votes Democratic increases by 1%, case rates fall by 6.38% and 0.95% per 100,000 before and after the election, respectively. This effect is statistically significant at the 1% level prior to the election. The negative slope aligns with my hypothesis that Democratic societies are composed of individuals who are more concerned about COVID-19 risk and thus practice more social distancing related behaviors. The larger magnitude in the pre-election model also aligns with my hypothesis of a magnitude differential between frameworks. This could be attributed to the virus' hold on urban metropolitan areas during the beginning of the pandemic.

The interaction of the threshold value and the running variable highlights how case rate trends differ for Democratically classified counties as a greater proportion of their population votes Democratic. With each 1% increase in the share of Democratic voters in already Democratic counties, case rates rise by 3.68% and 1.13% per 100,000 before and after the election, respectively. This means that as a moderate county leans Democratic in the 2020 election, it is associated with increasing virus transmission. Similar to the findings depicted in the graphical analysis, this evidence contradicts my hypothesis that Democratic societies are associated with lower virus levels. Instead, it provides a more nuanced interpretation of how political party affiliation affects public health in moderate counties. However, it is important to note that this effect is only statistically significant in the pre-election model.

The graphical regression discontinuity analysis illustrates that there is a change in case rate trends between Republican and Democratic counties. I estimate that as counties become Democratic prior to the election, case rates fall by 2.69% per 100,000, compared with an increase of 0.18% per 100,000 after the election. Performing a t-test between how increasing the Democratic vote share in either Republican or Democratic counties affects case rates illustrates that the decrease in case rate trends prior to the election is statistically significant. While both models depict a change in virus incidence as a greater share of the population votes Democratic, the magnitude of the associated change in virus cases is larger in the pre-election framework. This insinuates a correlation between improved nation-wide attitudes surrounding social distancing behaviors and a president who supports policies aimed at mitigating the consequences and spread of COVID-19.

Furthermore, Democratic leaning counties are correlated with lower case rates in both models. Case rates fall by 1.79% and 0.60% per 100,000 before and after the election, respectively. These findings align with my association of Democratic leaning counties with improved COVID-19 mitigating behaviors, but this effect is only statistically significant in the pre-election framework.

As the proportion of the population living near a park increases by 1% there is a statistically significant increase in case rates by 0.32% per 100,000 prior to the election. There is a near zero and statistically insignificant effect after the election. The statistically significant rise in case incidence with greater park access contradicts my hypothesis that parks promote social distancing behavior by offering individuals an opportunity to safely continue their normal interpersonal activities by socially distancing outdoors.

5. Conclusion

This paper investigates the intersection of political party affiliation and the built environment's relationship to COVID-19 case rates in the United States. I use the 2016 election returns to define pre-pandemic political leanings. Using the 2020 election returns, I measure how case rate trends diverge among moderate counties that lean slightly Democratic or Republican. Using the spatial relationship between a county population and its parks as a proxy for the urban landscape I measure whether greater access to parks contributes to more social distancing tendencies, as evidenced by case rate reductions. The data used includes publicly available COVID-19 case counts and U.S. Presidential Election results, which I merge with government reported features of the built environment, demographics, and COVID-19 regulations across all counties. This analysis can have far-reaching implications pertaining to how policy leaders design public health interventions depending on a community's political and environmental characteristics.

The OLS regression highlights a statistically significant correlation between voting Democratic in 2016 and higher case rates. Greater park access is associated with statistically significantly elevated case rates in Republican counties. Alternatively, in Democratic counties, greater park access is correlated with a slight reduction in case rates, but this effect is not statistically significant. The lack of a reduction in case rates given greater park access may illustrate that outdoor socializing does not perfectly equate to safe social distancing.

The regression discontinuity design illustrates that case rates fall as 2020 Republican counties lean Democratic. This effect is statistically significant in the pre-election framework, where case rates decrease at greater rates. Democratic counties are correlated with lower case rates, but as these counties lean decisively more Democratic, case rates rise. These effects are statistically significant prior to the 2020 election. Greater park access is associated with a statistically significant increase in case rates prior to the election and a statistically insignificant and near zero effect afterwards.

While this analysis expands the geographical scope of prior work, the level of observation of political party affiliation and the built environment is still too high to draw causal inference. Measuring political party affiliation in local, instead of national, elections may provide a more accurate proxy for a society's perceived COVID-19 risk levels. Additionally, counties in the United States span vast geographical areas, such that access to parks and associated activity choices differ greatly for residents of the same county. Furthermore, the use of cross-sectional data, due to accessibility constraints, hinders the ability to draw causal inference. To better specify the joint relationship between how political party affiliation and a county's urban landscape affect public health outcomes, future research should use proxies for political party affiliation and the built environment at a more granular level, while drawing upon pooled cross section or panel data to establish causality.

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7. Appendix

Figure A1. School Accessibility Given 2020 Voting Patterns

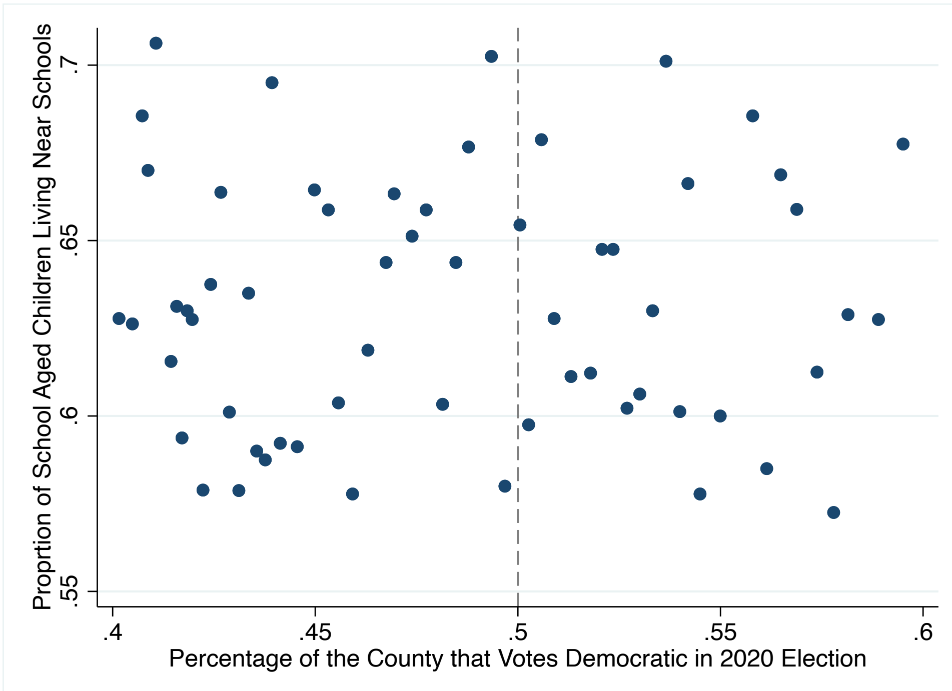


Figure A2. Schools Near Highways Given 2020 Voting Patterns

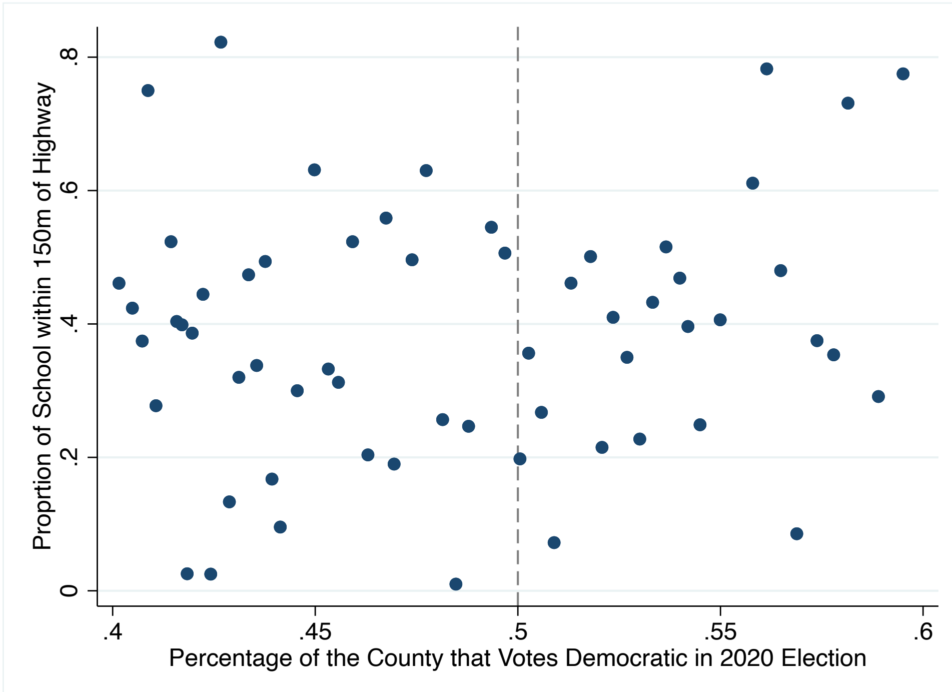


Figure A3. Commute Time: Driving 45+ Minutes Given 2020 Voting Patterns

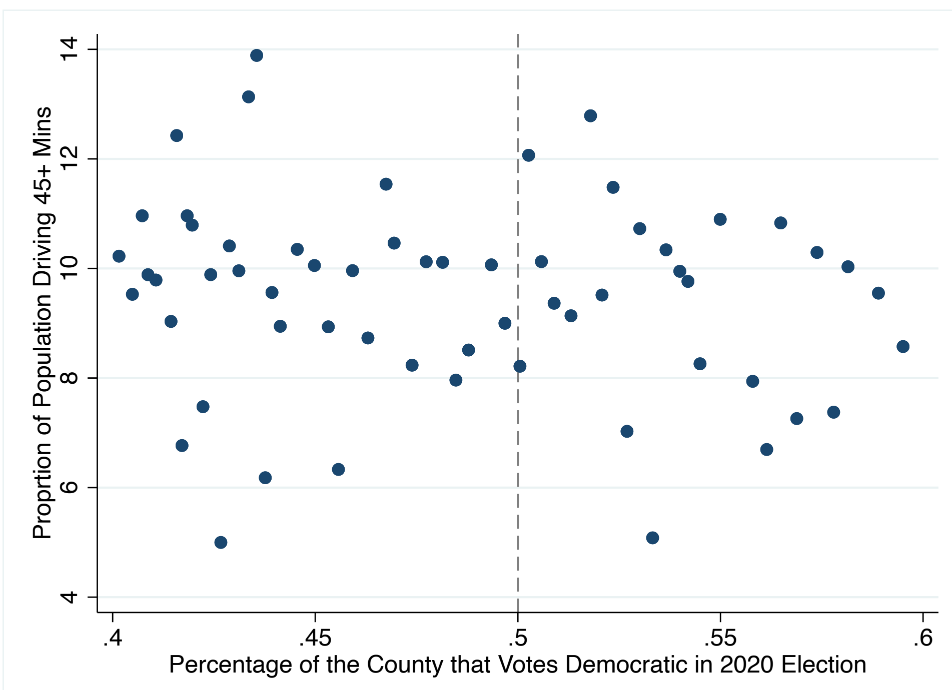


Figure A4. Commute Time: Using Active Transport Given 2020 Voting Patterns

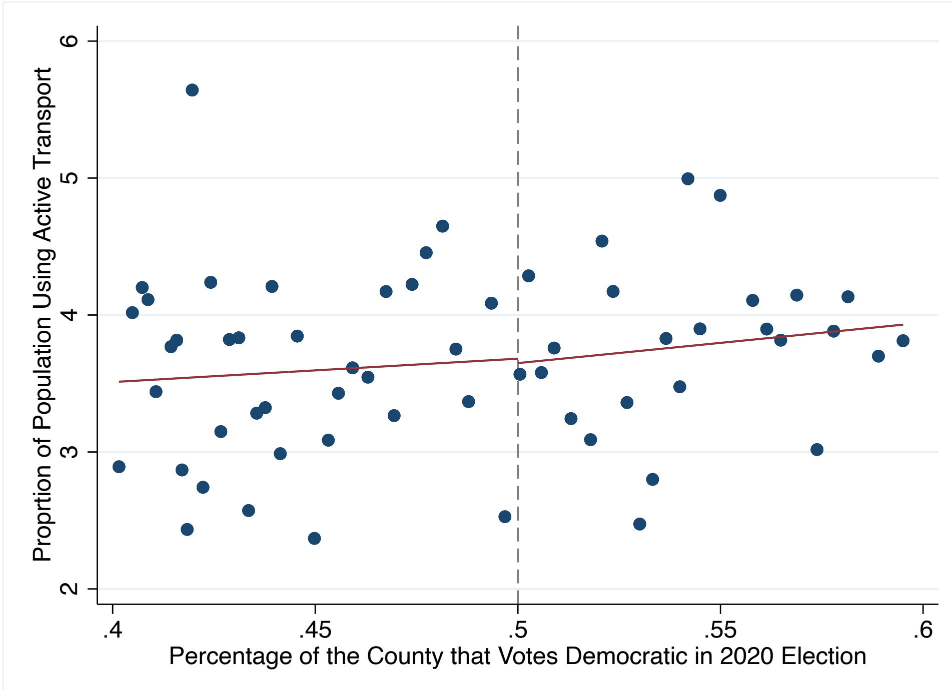


Figure A5. Commute Time: Taking Public Transport Given 2020 Voting Patterns

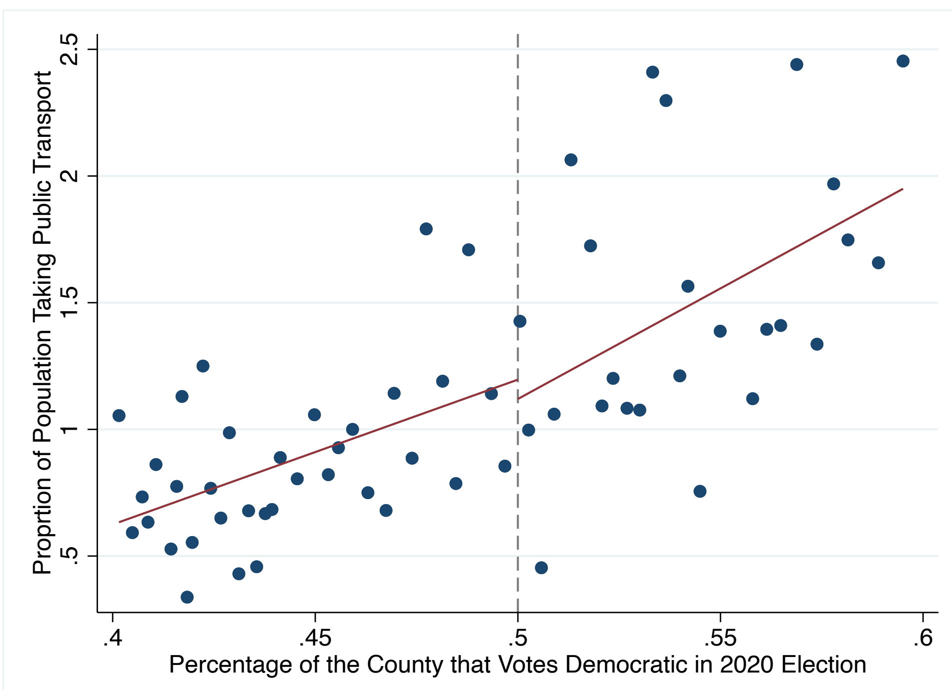


Figure A6. Gender Given 2020 Voting Patterns

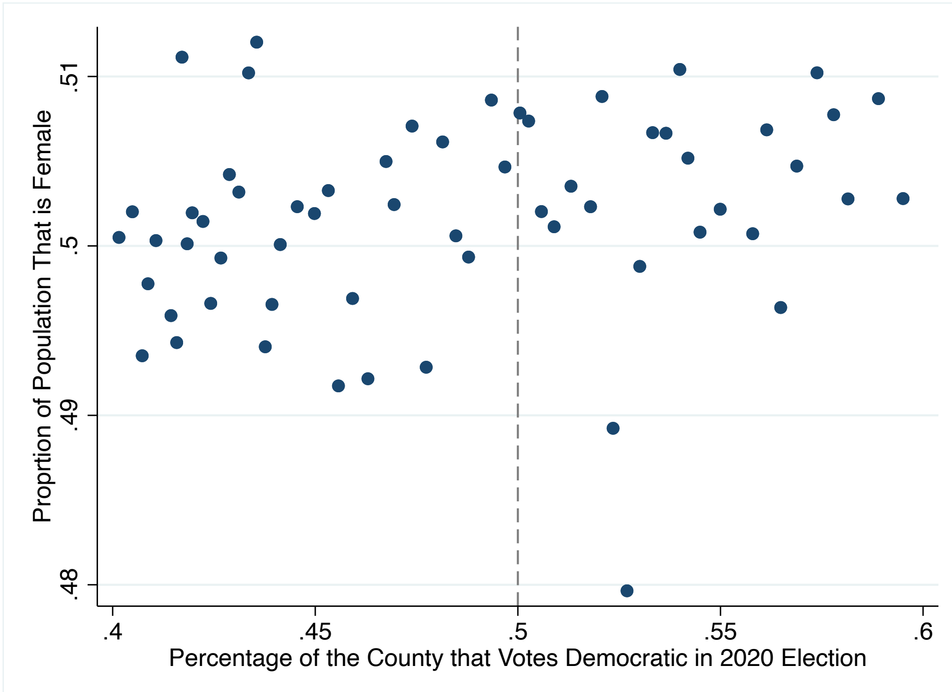


Figure A7. Race – White – Given 2020 Voting Patterns

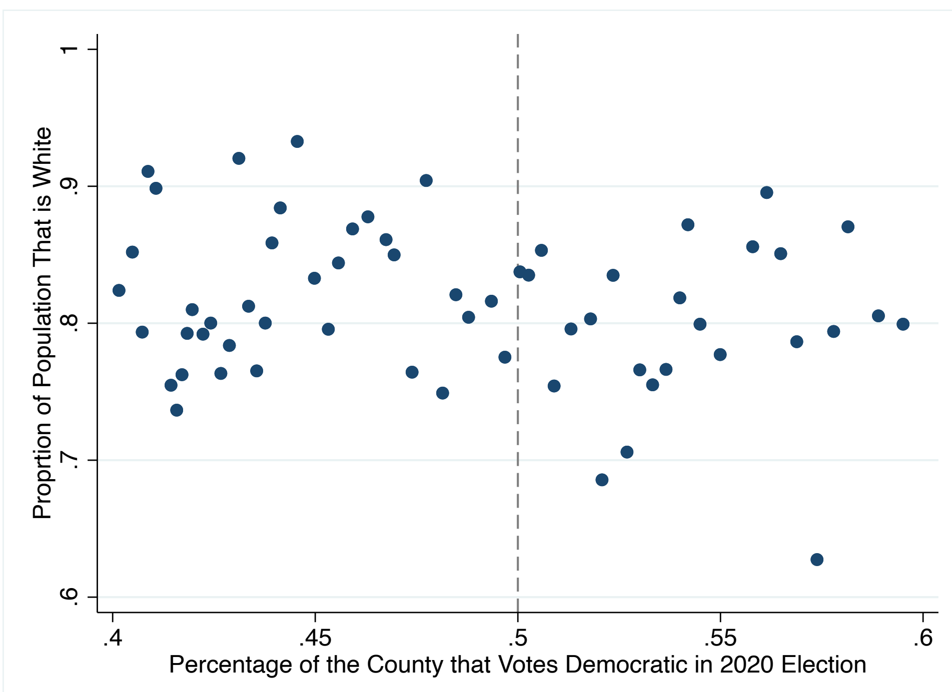


Figure A8. Race – Black or African American – Given 2020 Voting Patterns

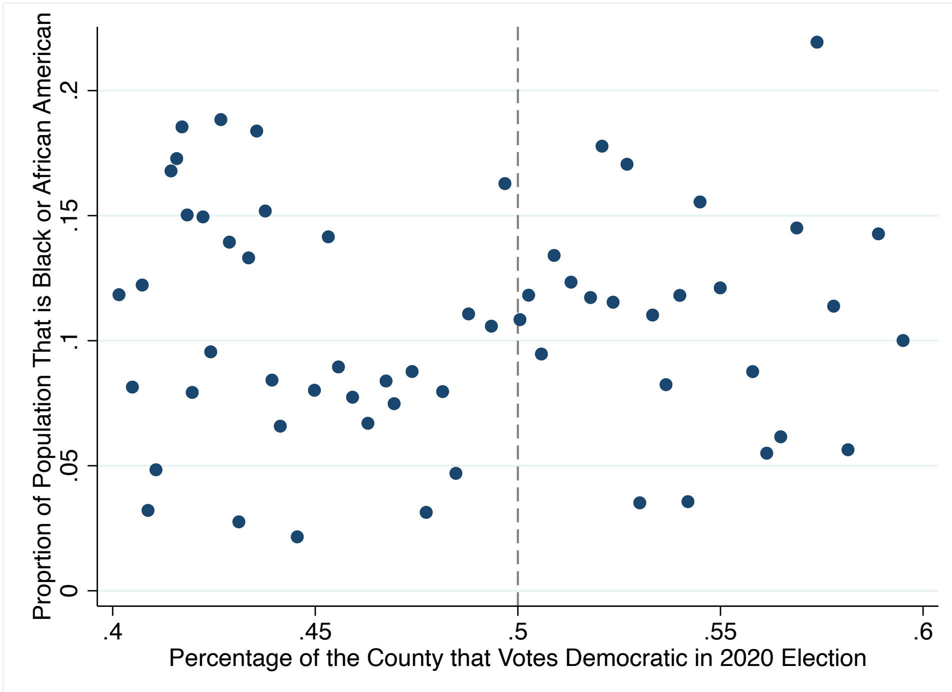


Figure A9. Race – Asian or Asian American – Given 2020 Voting Patterns

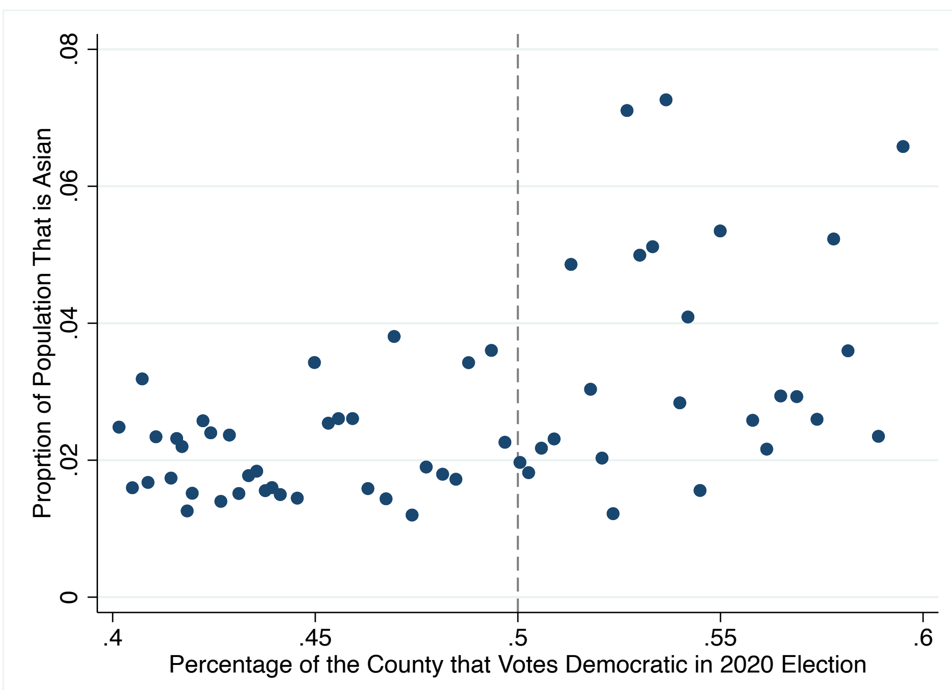


Figure A10. Education Levels Given 2020 Voting Patterns

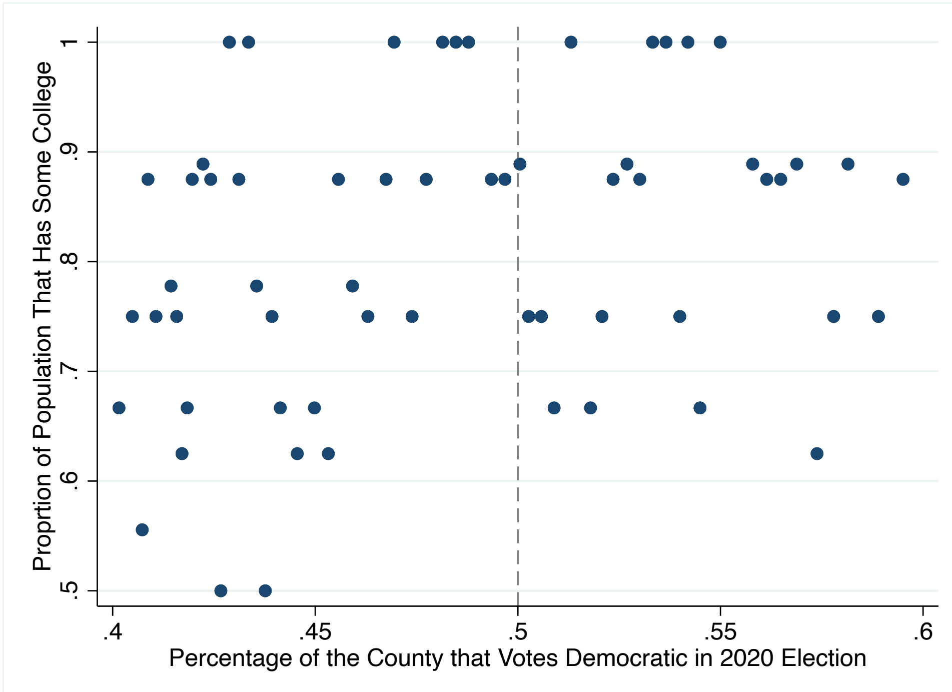


Figure A11. County Population Size Given 2020 Voting Patterns

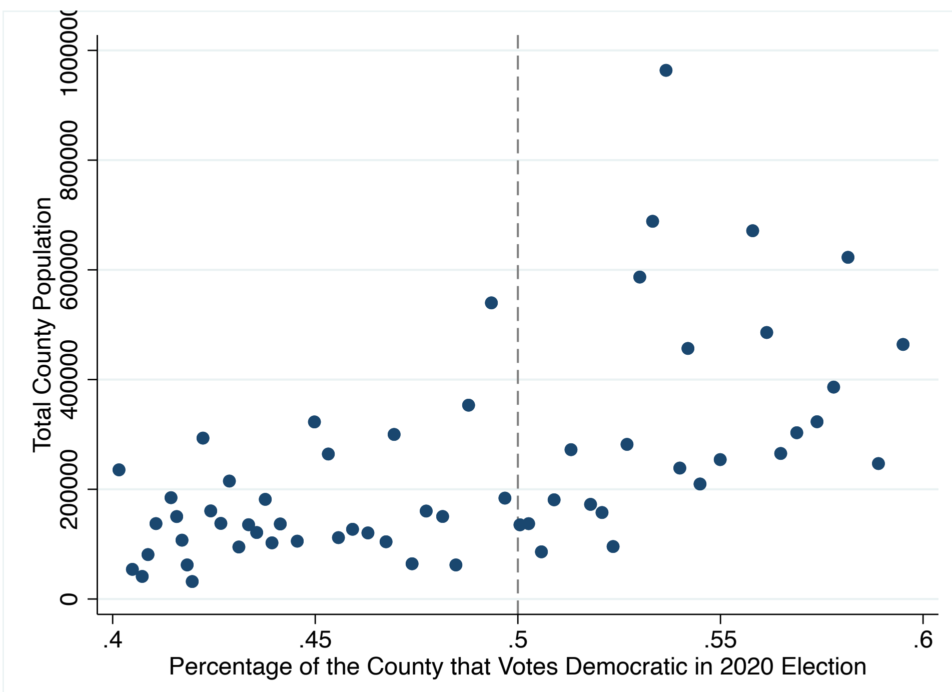
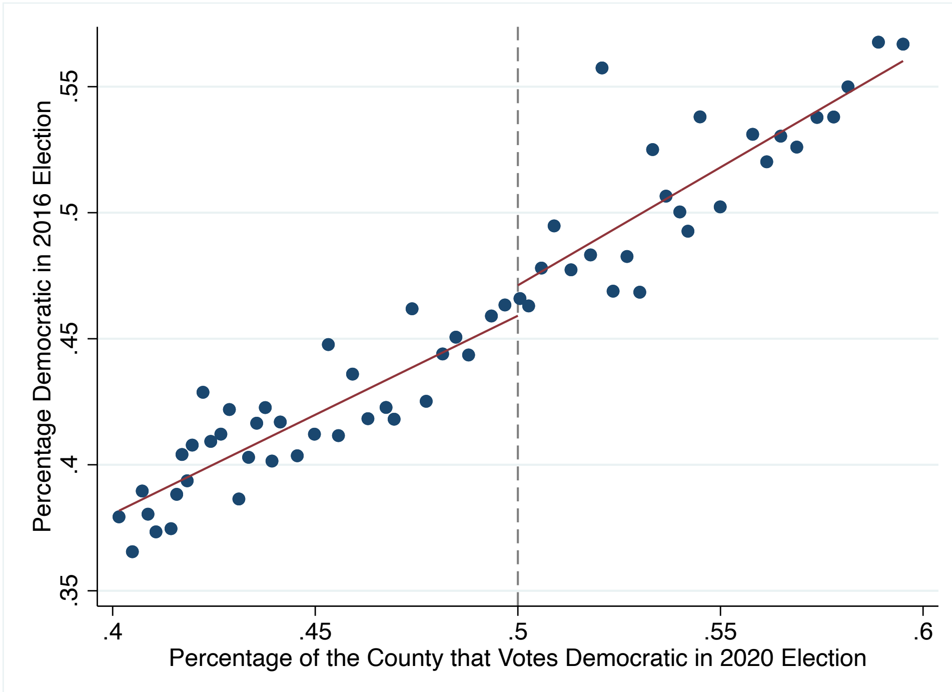


Figure A12. 2016 Voting Patterns Given 2020 Voting Patterns



Appendix Table 1A: OLS Regression, COVID-19 Cases	
Month-Year	All Counties
	Coefficient (Standard Error)
March 2020	-2.98*** (0.01)
April 2020	-2.23*** (0.01)
May 2020	-2.07*** (0.01)
June 2020	-1.84*** (0.01)
July 2020	-1.01*** (0.01)
August 2020	-0.85*** (0.01)
September 2020	-0.80*** (0.01)
October 2020	-0.31*** (0.01)
November 2020	0.51*** (0.01)
December 2020	0.78*** (0.01)
January 2021	0.65*** (0.01)
February 2021	-0.19*** (0.01)
March 2021	-0.74*** (0.01)
April 2021	-0.79*** (0.01)
May 2021	-1.16*** (0.01)
June 2021	-1.91*** (0.01)
July 2021	-1.32*** (0.01)

Note: ***p<0.01, **p<0.05, *p<0.1

Appendix Table 2A: Pre-Election Regression Discontinuity Design, COVID-19 Cases	
Month-Year	Coefficient (robust standard error)
March 2020	-2.85*** (0.08)
April 2020	-1.92*** (0.07)
May 2020	-1.78*** (0.06)
June 2020	-1.72*** (0.06)
July 2020	-0.94*** (0.06)
August 2020	-0.92*** (0.05)
September 2020	-0.91*** (0.04)
October 2020	-0.45*** (0.02)

Note: ***p<0.01, **p<0.05, *p<0.1

Appendix Table 3A: Post-Election Regression Discontinuity Design, COVID-19 Cases	
Month-Year	Coefficient (robust standard error)
November 2020	0.61*** (0.05)
December 2020	0.90*** (0.04)
January 2021	0.78*** (0.04)
February 2021	-0.02 (0.04)
March 2021	-0.42*** (0.05)
April 2021	-0.28*** (0.06)
May 2021	-0.81*** (0.05)
June 2021	-1.89*** (0.04)
July 2021	-1.39*** (0.02)

Note: ***p<0.01, **p<0.05, *p<0.1