Identity During a Crisis: COVID-19 and Ethnic Divisions in the United States*

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Abstract

During a crisis, does a community's ethnic composition influence policy efficiency? How do the effects of ethnic divisions differ from those of ethnic diversity? Despite the large body of work which considers ethnic composition, little attention has been given to how it matters for crisis-response policy. Using the lens of the COVID-19 pandemic in the United States, we show that ethnic divisions, rather than ethnic diversity, significantly reduced the efficacy of crisis response. U.S. counties with high levels of ethnic divisions fared worse than their less-divided counterparts after lockdowns in both COVID-19 cases and related deaths. Ethnic diversity had little effect, except in areas with high racial segregation. Crisis-response policies led to smaller mobility reductions and less mask-wearing in ethnically divided counties. These results are not driven by a lack of physical public goods, socioeconomic differences, population size, population density, political ideology, or by the prevalence of high-risk populations. Findings are robust to various strategies of causal identification and falsification checks. Our results suggest that policies promoting ethnic and racial integration can allay the negative social and economic impacts of crises.

Keywords: Ethnic Identity; Ethnic divisions; Diversity with(out) division; Racial segregation; Government Crisis-response; COVID-19; Lockdown Policies; Interpersonal Preferences; Prosocial Behavior

JEL Classification: I14, I18, H12, H75, J15.

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1 Introduction

A community's ethnic composition is one of its most salient features. This ethnic composition matters for a wide range of outcomes including the provision of public goods (Alesina et al. (1999)), economic development (Easterly and Levine (1997)), the stability of democracies (Horowitz (1993)), in-group loyalty and preferences for redistribution (Luttmer (2001)), and for minorities' outcomes (Cutler and Glaeser (1997), Boustan (2012)). And yet, despite the large body of work in political economy and public economics which investigates ethnicity, there has been little emphasis given to how ethnic composition matters for the efficacy of, and adherence to, government programs in times of crisis. In particular, it is difficult to disentangle the role played by *ethnic divisions*—a lack of unity, cohesion, and integration among different ethnic groups—from that played by *ethnic diversity*—the mere presence of multiple ethnic groups in a community—in such programs. In this paper, we examine both the distinct and the joint effects of ethnic divisions and ethnic diversity on the efficacy of government policies designed to address crises in which externalities play an important role. Notice that this notion of crisis extends to a large set of common ills - nearly all crises have the ability to be compounded or assuaged by externalities: bubbles can be inflated by noise traders; common resources may be depleted; communicable disease can be spread.

Importantly, by explicitly and distinctly considering the roles of ethnic divisions, ethnic diversity, and their interaction, we both distinguish ourselves from the extant literature and address the crucial question of how ethnic diversity matters in the presence (or absence) of ethnic divisions. Answering the latter is necessary for optimal policy design in multiethnic societies. We address these questions within the context of the COVID-19 pandemic, which is characterized by wide-scale externalities. The United States provides an ideal setting for two reasons. First, ethnic and racial divisions are prevalent and heterogeneously distributed across the United States. While some of the top-down causes of ethnic division in the United States have been repealed (e.g. Jim Crow laws, lending restrictions, legal constraints to integration), much ethnic division remains. According to a 2019 Pew poll, 58% of Americans say that race relations in the U.S. "are generally bad"; 65% of Americans say that racist views have been more commonly expressed since 2016.[1] Second, with over 28.1 million cases and $498,000$ deaths due to COVID-19, the United States is among the countries most strained by the COVID-19 pandemic.[2] Importantly, a striking feature of the disease burden in the U.S. is its highly unequal distribution across communities. These disparities suggest that structural factors, such as ethnic divisions, may be contributing to the spread.

We document how ethnic divisions in the United States have stifled the efficacy of crisis-response policies such as State of Emergency declarations, business and school closures, and safer-at-home orders. There are several reasons to consider the role of ethnic divisions in defining COVID-19 outcomes, especially in the U.S. where the formal enforcement of preventa-

[1] https://www.pewsocialtrends.org/2019/04/09/race-in-america-2019/

[2] Johns Hopkins University & Medicine Coronavirus Resource Center accessed on February 21, 2021 at https://coronavirus.jhu.edu/map.html.

tive policy measures has been weak. Since members of tight-knit communities have on average more repeated interactions, the Folk theorem suggests that these communities can sustain more prosocial behavior. In addition, a lack of communication between fragmented groups means that information about infection cases occurring in one group may not easily be transmitted to members of another group, making it less likely that precautionary actions will be taken in ethnically fragmented neighborhoods. Moreover, contact tracing may not be as effective in ethnically fragmented neighborhoods as it should be; residents of these areas may not know each other well. As others have found when examining preferences for redistribution (Alesina et al. (1999), Luttmer (2001)) and racial loyalty in giving (Fong and Luttmer (2009)), residents may be less altruistic towards out-group members. This implies lower incentives to self-quarantine or to wear a face mask for infected individuals living in more ethnically fragmented areas. These possible mechanisms suggest that both the quality and the efficacy of government measures implemented to combat COVID-19 spread may have been negatively impacted by the presence of ethnic divisions.

To test this hypothesis, we combine daily county-level data on confirmed COVID-19 cases and deaths compiled from the Centers for Disease Control and Prevention (CDC) by the non-profit organization USAFacts with data on government responses to the pandemic. Using the timing of crisis-response policies at the federal and county level, we implement a first difference and a double difference approach to estimate the causal impact of these policies and their interaction with ethnic divisions and ethnic diversity on COVID-19 outcomes. In addition to these two estimation approaches, we perform event-study analysis and in-time placebo robustness checks.

We find that *ethnic divisions*, rather than *ethnic diversity*, are an important and essential driver of the growth of COVID-19 cases and fatalities in the United States. Figures 1, 2 and 3 altogether illustrate this fact. In these figures, we consider two well-known measures of ethnic diversity and ethnic divisions—the ethnic fragmentation index (EFI) and a dissimilarity index measuring racial residential segregation.[3] Figure 1 shows the number of new COVID-19 cases and deaths over time separately in counties with above-median EFI and below-median EFI. While the number of new COVID-19 cases and deaths has significantly increased across the U.S., the increase has been much more significant in more ethnically fragmented counties. Figures 2 and 3 show that this effect is essentially driven by the role of racial residential segregation in highly fragmented counties. Figure 2 shows new COVID-19 cases and deaths over time in U.S. counties, disaggregated by above- and below-median levels of racial residential

[3]See Section 3 for a detailed description on how these measures are constructed. The ethnic (or ethnolinguistic) fragmentation index (EFI) has been used in economics to measure both *ethnic diversity* and *ethnic divisions* (c.f. Alesina et al. (1999) and Alesina and Ferrara (2005)). In this paper, we acknowledge both views. More precisely, we acknowledge that in societies that are *ethnically integrated*, EFI simply measures *ethnic diversity*. However, when society is organized around *segregated ethnic groups*, EFI can be viewed as a measure of disunity or ethnic divisions. Following this rationale in this paper, we consider EFI together with racial residential segregation. Indeed, the different processes leading to racial residential segregation in the United States (Boustan (2012)) imply that it captures a dominant facet of *ethnic divisions* in this country. Moreover, given that the correlation between EFI and racial residential segregation is very low in our dataset, there is significant variation in EFI in both racially segregated and racially integrated counties, which makes it possible to analyze how the effect of EFI varies by level of racial segregation.

segregation. There are significantly more cases and deaths in highly segregated areas. Finally, Figure 3 shows new COVID-19 cases and deaths over time in U.S. counties, disaggregated both by above- and below-median levels of EFI and racial residential segregation. It shows that EFI increases COVID-19 cases and fatalities primarily in counties that display a sufficiently high level of racial segregation. Put differently, ethnic diversity matters little, except in racially segregated counties.

Our regression-based analyses establish that these observations describe a causal relationship. We find that while mobility restrictions have been effective in slowing the spread of COVID-19 and in averting deaths, they have been much less effective in ethnically fragmented counties in both absolute terms and in terms of the number of negative outcomes per county resident. First using a simple pre-post analysis, we show that the federal State of Emergency declaration was only $\frac{1}{50}$ as effective in preventing deaths in counties in the highest quintile of ethnic fragmentation as it was in the counties in the lowest quintile of ethnic fragmentation. Following the federal State of Emergency declaration there were 203 more cases of COVID-19 per $100,000$ inhabitants and 9 more deaths per $100,000$ inhabitants in counties in the highest quintile of EFI than in counties in the lowest quintile. These findings are confirmed using an index of stringency of government responses to COVID-19. This pre-post comparison, however, should be interpreted with caution as it lacks a proper counterfactual. We circumvent this issue with a second empirical strategy that exploits cross-county variation in the timing of county-level State of Emergency declarations in a difference-in-differences setting to document the causal effect of county-level preventative policies on COVID-19 outcomes. Consistent with the results of the federal policy, we find that following the county-level emergency declaration there were 167 more cases of COVID-19 per $100,000$ inhabitants and 7 more deaths per $100,000$ inhabitants in counties in the highest quintile of EFI than in counties in the lowest quintile. These findings are robust to considering other county-level crisis-response policies such as safer-at-home and business closure orders. Importantly, we show that our findings are not driven by a lack of physical public goods, socioeconomic differences, or by the prevalence of high-risk populations in more fragmented counties.[4]

Our analysis furthers the idea that *ethnic divisions* rather than *ethnic diversity* spurred disease spread during the COVID-19 pandemic. While the ethnic (or ethnolinguistic) fragmentation index has been used to measure both ethnic diversity and ethnic divisions (c.f. Alesina et al. (1999) and Alesina and Ferrara (2005)), we argue that the two are not necessarily equivalent. Ethnic diversity can exist without ethnic divisions, especially if members of different ethnic groups are integrated (Bazzi et al. (2019)). It follows that while the existence of ethnic divisions implies that of ethnic diversity, the converse may not be true. In communities where

[4]Indeed, our findings are highly robust to controlling for a wide range of factors such as total population, population density, percentage of males, average age, poverty, percentage of adults with at least a high school degree, percentage of urban population, percentage of population born outside of the United States, political ideology or polarization (measured by the share of Trump voters in the 2016 presidential election), and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Moreover, using the residual from a fitted regression between EFI and these variables, we find that a large proportion of the variance in EFI is explained by the residual. This implies that our findings are less likely to be driven by a high prevalence of COVID-19 related risk factors in high EFI counties.

ethnic groups are sufficiently integrated, the above-mentioned channels through which ethnic fragmentation can affect the spread of COVID-19 may not operate. This implies that ethnic diversity will have little effect in ethnically integrated communities. In order to test this hypothesis, we analyze how the effect of EFI differs by level of racial residential segregation in a county. As illustrated by Figure 3, we find that EFI increases COVID-19 cases and fatalities and constrains the effectiveness of crisis response policies mainly in counties that display a sufficiently high level of racial segregation. When the level of racial segregation is low, EFI has very little impact on these outcomes. Indeed, following President Trump's State of Emergency declaration, moving from the lowest quintile of the ethnic fragmentation index to the highest quintile of EFI within the set of the most racially segregated counties is associated with, on average, 270 more COVID-19 cases per $100,000$ inhabitants and 13 more associated deaths per $100,000$ inhabitants; in the least segregated counties these outcomes are 149 and 5, respectively. These findings strongly support the idea that a lack of cooperation between members of different ethnic groups is driving the effects of ethnic fragmentation. By limiting interracial interactions, segregation makes undertaking collective actions to curb the pandemic and mitigate its consequences difficult.

Salient examples of U.S. counties where high levels of COVID-19 incidence, ethnic diversity, and ethnic divisions coincide include counties which contain large cities such as Los Angeles, New York City, and Chicago. The reader may then inquire if the link between ethnic divisions and disease incidence that we observe is in fact being driven by the impact of COVID-19 in large cities, many of which are also diverse. In fact, our effect is persistently observed across U.S. counties of varying populations—both ethnic fragmentation and racial segregation are positively and statistically significantly correlated, at the .0001 level, with daily cases of COVID-19 within each quintile of population. For an example, consider the small county of Nobles Minnesota, with a total population of 21,839. Nobles County is more ethnically heterogeneous than 87 percent of remaining counties, is more racially segregated than 86 percent of remaining counties, and ranks fourth highest in cases of COVID-19 per resident. Ultimately, our findings are not driven by population size or density, as these factors are controlled for in our analysis[5].

These results suggest that the ability of communities to take actions to limit the spread of the novel coronavirus — keeping distance between members of different households, maintaining distance from sick persons inside and outside the home, and wearing face-coverings in public — is negatively impacted by ethnic fragmentation, and even more so by racial residential segregation. Importantly, we test and validate these underlying mechanisms. In addition, we find that the negative effects of ethnic divisions on preventative behaviors persist even when controlling for socioeconomic differences and differences in aggregate health measures. There are several explanations consistent with these findings. Where ethnic divisions are present,

[5] In regressions where the absolute level of COVID-19 cases and deaths are the dependent variables, we include population levels and density as control variables. We also include regression estimates using of cases of COVID-19 per 100,000 residents and deaths of COVID-19 per 100,000 residents. In these specifications, we control for population density (see Appendix Tables XXXX)

communities behave less prosocially and provide public goods less efficiently. They also sanction less effectively. Consistent with the former mechanism, we find that mobility reductions and mask wearing are negatively impacted by ethnic fragmentation and residential segregation. The latter mechanism is supported by an additional finding that ethnic fragmentation negatively affects the likelihood of belonging to a social association only in racially segregated counties.

Our first contribution is to the literature on the effect of ethnic composition on social and economic outcomes. Within this literature, our paper is among the first to examine how ethnic divisions affect government crisis response. It is also the first paper to explicitly analyze the separate and joint effects of *ethnic divisions* and *ethnic diversity* and to show that ethnic diversity matters little in the absence of ethnic divisions (as measured by racial segregation). This latter finding is consistent with other work showing that in a situation of crisis, ethnicity matters little for giving behavior, unless individuals who give feel close to their racial or ethnic group and the victims are of the same group (Fong and Luttmer (2009)).

We also contribute to a growing literature which underscores the importance of race in shaping the economic and disease burden from COVID-19 (c.f. Andrasfay and Goldman (2021), Pongou et al. (2020)). Finally, we contribute to a body of work which emphasizes the importance of social attitudes in mitigating the spread of COVID-19. Bonaccorsi et al. (2020) find that restriction measures were successful at reducing mobility. Müller and Rau (2020) find that pre-crisis indicators of social responsibility positively predict compliance with COVID-19 preventative policies. Barrios et al. (2021) use mobility and survey data to find that adherence to mask-wearing and social distancing in the United States and some regions of Europe is positively predicted by pre-crisis measures of civic capital. Durante et al. (2020) find similar results for the importance of civic capital in Italian provinces. Finally, Ding et al. (2020) find that demonstrated willingness to engage in costly social good provision predicts increased social distancing behavior in the United States.

Our paper significantly differs from the aforementioned studies in its scope, analyses, and policy implications. In fact, we are instead interested in disentangling the role of *ethnic divisions* from that played by *ethnic diversity* in the efficacy of government response to crises involving wide-scale externalities. We find that national and county emergency declarations were successful at increasing self-quarantining during the COVID-19 crisis in the United States: mobility levels, including visits to workplaces, transit stations, retailers and recreation outlets, dropped following emergency declarations. A distinctive feature of our analysis, however, is that we show that the efficacy of the emergency declarations was lower in counties with high levels of ethnic fragmentation. Most importantly, we find that the efficacy of national and county-level policies in curbing the spread of COVID-19 and averting COVID-19 deaths was low mostly in ethnically fragmented counties that are also racially segregated. In addition, residents of more ethnically divided counties were less likely to report wearing face masks. Our findings therefore lead to the conclusion that *ethnic divisions*, rather than *ethnic diversity*, spurred drastic differences in COVID-19's impact. Our paper is the first to document these results.

Our results and proposed mechanisms suggest that federal policy making and enforcement, which can circumvent local coordination problems, could be a good approach to ensure that best practices are followed. Our analysis also suggests that designing, implementing, and sustaining policies of ethnic and racial integration can improve the efficacy of government crisis-response.

The rest of the paper is organized as follows. Section 2 presents the conceptual framework. Section 3 describes the data used in the analysis. Section 4 presents the identification strategy, and Section 5 presents results. Section 6 investigates the different channels through which mobility restrictions and other preventative policies operate. Section 7 concludes.

2 Conceptual Framework

For most people, the choices to stay home in the event of fever, avoid socialization, and to wear awkward and uncomfortable face coverings are simply not rationalizable under purely self-interested preferences with reasonable levels of risk tolerance. Instead, these choices generate important externalities which benefit others; they are public goods. In the United States, government policies to address these externalities have been decentralized and patchworked across states and localities. County-level safer-at-home orders were unfurled across the country at a variety of different times and with varying levels of restrictiveness. For example, at their most restrictive levels, in some counties masks remained optional and gathering sizes remained unlimited. Other counties instituted strict mask requirement, business closing, and gathering size restrictions.[6] Further, conditional on violating one of these policies, the likelihood of receiving a formal sanction for this violation is low.

Because group-level coordination underpins both policy formation and adherence, ethnic divisions may have impacted counties' public good provision during the COVID-19 crisis through multiple channels. First, ethnic divisions have been linked to an inability to issue effective social sanctions in both developed and developing contexts (Miguel and Gugerty (2005), Algan et al. (2016)). For example, using data from the United States, Algan et al. (2016) find that ethnic divisions in French public housing hamper members of a community from sanctioning one another for vandalism. Since local face-covering, travel, and social-distancing guidelines are only imperfectly enforceable by formal authorities, norms and social sanctions make these policies more effective. Second, if ethnic divisions in a county lead individuals to interact infrequently, it will be more difficult for county-level prosocial behavior to be sustained. Cooperation is easier to sustain when individuals carry reputation and when they expect to interact more often in the future (Maskin et al. (1994), Kreps and Wilson (1982)). Third, to the extent that social distancing and mask-wearing are public goods, ethnic divisions may decrease private contributions to such goods by lowering the manifestation of racial group loyalty. For example, using survey data from the United States, Luttmer (2001) find that individuals are less likely to support welfare spending as the share of local recipients from their own racial group de-

[6] ProPublica has reported on the the extreme heterogeneity in county-level responses to the pandemic: https://www.propublica.org/article/states-with-few-coronavirus-restrictions-are-spreading-the-virus-beyond-their-borders

creases. Also, using experimental data, Fong and Luttmer (2009) find that racial group loyalty positively affects giving to victims of Hurricane Katrina. A fourth potential mechanism arises from the potential for ethnic divisions to limit communication between groups. If some segment of a county's residents do not communicate with one another, the ability of that county to provide mutually beneficial public goods will be hampered (Ellingsen and Östling (2010), Ostrom and Walker (1991), Ostrom et al. (1992), Leibbrandt and Sääksvuori (2012)). Contact tracing will be ineffective and knowledge about transmission will be sub-optimally shared (for a meta-analysis of the effect of communication on cooperative behavior which spans several disciplines, see (Balliet, 2010)). Finally, preference heterogeneity may have impacted counties' ability to solve coordination problems, although *a priori* the effect of preference heterogeneity on communities' ability to coordinate is ambiguous.[7]

Each of the mechanisms above — decreased sanctioning power, decreased prosociality, decreased communication — are affected by a community's ethnicity only inasmuch as ethnicity in that community defines and limits social relations. Where diversity and close personal contact between groups coexist, these mechanisms do not operate. For example, in a field experiment among Norwegian soldiers, Finseraas et al. (2019) find that soldiers randomly assigned to live with ethnic minorities display higher levels of trust toward members of immigrant communities. Following an Indonesian resettlement program, Bazzi et al. (2019) find that, while the level of local diversity is associated with increased willingness to contribute to village public goods and a decreased likelihood of ethnic conflict, this effect is dampened by residential segregation. Alesina and Zhuravskaya (2011) find that countries where ethnic groups are more residentially segregated have lower levels of trust and lower quality of governance. Several other scholars in economics and political science have highlighted similar results. Miguel (2004) notes that while ethnic diversity is associated with lower public goods provision in Kenya, this is not the case in Tanzania. Noting the arbitrary colonial-era boundary between the similarly diverse countries, he argues that the key differentiator is that the postcolonial Tanzanian government employed a large policy agenda to promote inter-ethnic dialogue and interaction while the Kenyan government employed no such policy. Ejdemyr et al. (2018) find that segregation enables politicians to preferentially target funds to co-ethnics' districts. Segregation in the electoral districts, rather than diversity, matters for the provision of new wells in Malawi. This effect of segregation persists despite controlling for the level of diversity in the district.

We therefore consider two measures of ethnicity in U.S. counties. The first, the Herfindahl diversity index, is increasing in the number of ethnicities present in a given county. This measure is the most common in the literature exploring the importance of ethnic divisions for public good provision (c.f. Alesina et al. (1999)). While this measure has been used in the

[7]While the idea of preferences which are correlated with ethnicity is posited to impact ethnic divisions (Alesina et al. (1999)), the empirical evidence around this point is mixed. For example, Desmet et al. (2017) find that, while preferences around norms, attitudes, and values are correlated with ethnicity, within-ethnicity variation in cultural attitudes is greater than that between ethnicities. Nonetheless, if there is cultural transmission of preferences, ethnically diverse counties may face a more difficult time coordinating to form policy (as was found by Beach and Jones (2017)). Conversely, if the legislative production process benefits from a diversity of preferences and skills (Alesina and Ferrara (2005); Fafchamps (2000)), then the impact of ethnic divisions on the quality of policies designed during the pandemic may be positive.

literature to proxy for ethnic division or fractionalization, we emphasize that the construction of this measure captures the number of ethnic groups present and not necessarily the level of divisions between them. In and of themselves, the ethnicities of a county's residents are, of course, neither a hindrance nor a help to the spread of the novel coronavirus. We therefore also consider a second measure - white-non-white residential segregation as measured by a dissimilarity index.[8] This measure of residential segregation captures the level of evenness with which the residences of non-white residents are dispersed among those of whites. Residential segregation as captured by a dissimilarity index increases as residential patterns deviate further from a random residential allocation. Contemporaneous residential segregation is a direct product of ethnic divisions both in its top-down causes (i.e. historical exclusion of minorities from certain areas through legal and racial restrictive covenants, lending restrictions, discrimination in the housing market), and in its bottom-up causes (i.e. preference-based sorting). These different factors are surveyed in Boustan (2012)). In particular, evidence for preference-based sorting including the "white flight" phenomenon is provided in Card et al. (2008), Boustan (2010), and Baum-Snow and Lutz (2011), and racial discrimination in the housing market is documented in Page (1995) and Hanson and Hawley (2011).

Under racial residential segregation, members of different ethnicities interact less frequently and are therefore more divided. For example, Sigelman et al. (1996) conduct a survey of the residents of Detroit, one of the most segregated cities in the United States. They find that contact between black and white residents is most frequently brief, casual, and non-intimate. Larger-scale empirical research underscores the relationship between residential segregation and ethnic divisions. School children living in more racially segregated areas are more likely to have ethnically segregated friendships (Mouw and Entwisle (2006)). Americans living in racially segregated areas are more likely to rely on racial stereotypes and media portrayals when forming their opinions of non-coethnics. Residents of highly segregated areas are also more likely to report higher instances of racial prejudice and feelings of racial competition (Eric Oliver and Wong (2003)).

We therefore anticipate that ethnic divisions negatively impacted the efficacy of policy responses to the COVID-19 crisis. Ethnic diversity will negatively affect COVID-19 outcomes mainly in areas with greater level of racial segregation. In addition to these hypotheses, we test the proximate mechanisms through which ethnic divisions affect COVID-19 outcomes.

3 Data and Descriptive Statistics

For this study, we combine different datasets covering the period between February 1, 2020 and June 7, 2020. We focus on this period to be able to identify the "causal" effects of early federal and county-level policy responses to the COVID-19 pandemic and analyze how these effects interact with ethnic divisions. We end data collection at June 7, 2020, after which some

[8]We focus on white-non-white segregation here as this measure of residential segregation has been the focus of economists studying the role of segregation in the United States. Our main results, however, replicate when we consider a dissimilarity index of residential segregation between whites and blacks.

county-level preventative policies were rescinded and new, overlapping, policies were introduced elsewhere. Analyzing data beyond June 7, 2020 raises the concern of attributing the effects of overlapping policies to early lockdown measures. Data include COVID-19 related cases and deaths, government policies, physical distancing, and socio-demographic characteristics. In this section, we describe the main data sources and highlight the general patterns in the data.

Data on COVID-19 cases and deaths. We obtain county-level daily data on new and cumulative confirmed COVID-19 cases and deaths from USAFacts. USAFacts is a private non-profit group that compiles data from the United States Centers for Disease Control and Prevention (CDC) and from state and local public health agencies. The USAFacts dataset on COVID-19 cases and deaths is a time series database spanning the period from January 22, 2020 to June 07, 2020 (the latest date available at the time the data was downloaded). The cumulative number of confirmed cases is updated each evening. Not every case is reported by county; some are not allocated due to lack of information. The number of missing observations is too small to bias our results (0.73% of observations are missing across all county-days).

Data on national and sub-national government responses to COVID-19. With the spread of COVID-19, federal and local governments in the United States have implemented various non-pharmaceutical interventions. At the federal level, a national emergency was declared by the White House on March 13, 2020.[9] This declaration increased the level of federal funding available for states and localities to respond to the crisis and to expand the scope of their emergency actions as the COVID-19 outbreak continued. We exploit this date to construct a proxy for national emergency declaration, a dummy which equals one on or following the day of the declaration and zero otherwise.

Another metric for national governments' response to COVID-19 crisis is the stringency index obtained from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al. (2020)), which collects information on a range of physical distancing measures, assigns a score for the measure, and then aggregates this information into a composite stringency index. The stringency index is based on nine response indicators including school closings, workplace closings, the cancellation of public events, restrictions on gathering sizes, closing of public transportation, safer-at-home requirements, restrictions on internal movements and restrictions on international travel. Indicator values are aggregated and rescaled to values from 0 to 100, with a higher index indicating a stricter combination of measures. Importantly, *strictness* is distinct from effectiveness. This index simply records the number and stringency of government policies. The index's authors caution that index scores "should not be interpreted as 'scoring' the appropriateness or effectiveness of a country's response".[10] Further details on the OxCGRT database are provided in Hale et al. (2020).

[9] Availableathttps://www.whitehouse.gov/presidential-actions/proclamation-declaring-national-emergency-concerning-novel-coronavirus-disease-covid-19-outbreak/

[10] From data description available at https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker/

At the county level, data on policy response to COVID-19 are retrieved from the National Association of Counties (NACO).[11] NACO collects a wide range of information on local governments' actions to mitigate the spread of COVID-19, including the onset of county-level emergency declarations and mobility restrictions in response to COVID-19. We construct three measures of sub-national government response to COVID-19 using NACO's information on the dates of county-level implementation of: 1) State of Emergency declarations; 2) closure of all non-essential businesses; and 3) safer-at-home orders, which call for residents to remain at home. Each measure is defined by a dummy equal to one on or following the day of a given policy response and zero otherwise.

Data on social distancing. To capture social distancing behavior we rely on mobility variables compiled by Google Community Mobility reports. These data are collected from users who have opted-in to having their location history tracked by Google. Data have been temporarily made available by Google during the pandemic. These reports compile data on the percent change in visits to different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residences. The mobility data show how visits and duration of stay changed relative to a baseline for the same areas and same day of the week prior to the virus spread. We extract daily data on mobility from February 15, 2020 to May 29, 2020.

Measuring Ethnic Fragmentation. The American Community Survey (ACS) collects information about the ethnic and racial composition of the population.[12] Respondents are asked if they belong to any of the following population groups: Hispanic, White, Black, Native American, Asian, Pacific Islander, and Other. We use this information along with the Herfindahl diversity formula to compute an index measuring the degree of county-level ethnic fragmentation.[13] This index measures the probability that two randomly selected individuals from the same county belong to two different ethnic groups. Specifically, our index of ethnic fragmentation is calculated using the formula:

$$\mathsf{EFI} = 1 - \sum_{r=1}^{e} \frac{(\mathsf{N}_r)^2}{\mathsf{N}^2} \tag{1}$$

Where *EFI* refers to Ethnic Fragmentation Index, e corresponds to the number of ethnic groups listed, N_r the size of ethnic group r in the county, and N the county population total. As EFI increases, the likelihood that two randomly selected individuals belong to the same ethnic or racial group decreases. As EFI increases, so does the level of ethnic fragmentation in a given community. The spatial distribution of EFI for U.S. counties as of the 2018 ACS is shown in the top map of Figure A1. This map shows that EFI varies widely across U.S. counties.

[11] Available at https://www.naco.org/covid19/topic/research-data

[12] For all analysis involving ACS data, we rely on the 2018 round of the American Community Survey, the most recent year for which data is available.

[13] This approach is widely used in the literature. See for example Mauro (1995), Easterly and Levine (1997), Alesina and La Ferrara (2000), and Pongou (2009).

Measuring racial residential segregation. A widely used measure of residential segregation is the dissimilarity index (Duncan and Duncan (1955); Massey and Denton (1988); Iceland et al. (2002); Boustan (2012); Graham (2018)).[14] Our focus in this paper is on residential segregation by race, information drawn from the ACS. The dissimilarity index is a measure of the evenness with which two groups (either blacks and whites or whites and non-whites in our case) are distributed in a given area (a census tract in the case of the ACS). Conceptually, the white-vs-non-white dissimilarity index, which ranges from 0 (complete integration) to 100 (complete segregation), measures the percentage of a group's population that would have to move to different geographical areas (census tracts) in order to produce a distribution that matches that of the metropolitan area overall (counties in the ACS). This index therefore shows to what extent two subgroups are isolated from one another. In the literature, the Dissimilarity Index (DI) is given by the formula:

$$\mathsf{DI} = \frac{1}{2}\mathsf{E}[|\frac{\mathsf{s(Z)}}{\mathsf{Q}} - \frac{1-\mathsf{s(Z)}}{1-\mathsf{Q}}|] \tag{2}$$

where Z is the proportion of census tract z that is minority and Q is the county-wide frequency of minority residents. Graham (2018) shows that DI equals the proportion of a county's minority residents who would need to move in order to achieve perfect residential integration, *relative* to the proportion of a perfectly segregated county's residents that would have to move to achieve perfect residential integration.

The spatial distribution of the racial residential segregation index for U.S. counties as of the 2018 ACS is shown in the bottom map of Figure A1, which highlights the differences in the spatial distributions of ethnic fragmentation and racial segregation. While the existence of within-county racial segregation implies residents of multiple races, the converse is not true. Some racially diverse counties are integrated, while others are not. Indeed, the correlation between EFI and the dissimilarity index measuring racial segregation between whites and non-whites is merely 0.0052. We show that in communities where ethnic groups are sufficiently integrated, the channels through which ethnic fragmentation affects COVID-19 outcomes do not operate. This implies that ethnic diversity has little effect in less segregated communities.

Other social and economic characteristics. Demographic and economic variables come from the ACS. Throughout, all socio-economic variables are an average across five years of ACS data collection ending in 2018. For the purpose of this paper, the following county-level statistics and indices are extracted from the ACS: population size, population density, unemployment rates, foreign-born population, gender distribution of population, average age of the population, educational attainment, urban-rural distribution of the population, and poverty rates. We also use information about the health characteristics of counties including the percentage of adults reporting: fair or poor health, smoking, obesity, and diabetes. We also control for political ideology and polarization, measured by the share of Trump voters in the 2016 presidential

[14] Massey and Denton (1988) identified five measures of residential segregation: dissimilarity index, isolation index, delta index, absolute centralization index, and spatial proximity index.

election at the county level.

To examine the relationship between ethnic divisions, ethnic diversity, government response to the pandemic, and COVID-19 cases and deaths (measured both in terms of levels and rates) , we merge the datasets described above and drop daily observations with missing EFI, confirmed cases of COVID-19, or government policy indexes. The refined sample consists of 433,872 daily observations from 3,143 counties spanning the period from January 22, 2020 to June 07, 2020. Table 1 reports descriptive statistics of the variables of interest in our sample.

4 Identification Strategy

To assess the causal impact of ethnic divisions, government policy, and their interaction on COVID-19 cases and fatalities, we rely on two main methodologies. The first approach is a pre-post analysis that exploits the timing of the federal State of Emergency declaration to compare the main outcomes of interest before and after the policy announcement. This approach is useful because the policy does not vary at the county level for a fixed date. However, it lacks an appropriate comparison group in the post period. We therefore advance our analysis using a difference-in-differences (DiD) strategy which evaluates the efficacy of staggered county-level mobility restrictions.

Under the DiD strategy, counties that did not implement mobility restriction policies serve as counterfactuals for counties that did. This strategy exploits the differential timing of policy implementation and controls for various confounding factors, making it possible to identify the causal impact of mobility restrictions. In addition to these two approaches, we perform an event-study analysis and an in-time placebo robustness check.

4.1 First Approach: Pre-post Analysis

Using the federal State of Emergency declaration, we first implement a simple pre-post analysis at the national level. Specifically, we estimate the following OLS regression:

$$\begin{aligned} \mathsf{Covid}_{cst} = \lambda_0 + \lambda_1 \mathsf{NationalPolicy}_t + \lambda_2 \mathsf{EFI}_{cs} + \lambda_3 \mathsf{NationalPolicy}_t \times \mathsf{EFI}_{cs} \\ + \alpha_z + \delta_t + \mathbf{X}_{cs}^{'}\pi + \varepsilon_{cst} \end{aligned} \tag{1}$$

Where Covid_{cst} is the outcome of interest, which is alternatively the number of COVID-19 cases and deaths in county c of state s on date t.[15] $\mathsf{NationalPolicy}_t$ refers to the United States federal government's response to the pandemic. This variable is measured in two ways. First, we exploit the timing of the national emergency declaration to define $\mathsf{NationalPolicy}_t$ as a dummy equal to one for dates t greater than or equal to March 13, 2020 (the date on

[15] In Section 5, we also analyze the relative number (or rate) of COVID-19 cases/deaths, defined as the number of cases/deaths divided by the total population of a county.

which the White House declared a federal State of Emergency), and zero otherwise. In a second specification, we use the Ox-CGRT stringency index which records how the strictness of the federal policy response has varied over the course of the pandemic (see description of this variable in the data section). In this case, $\mathsf{NationalPolicy}_t$ is a continuous variable taking a value between 0 and 100. The next regressor, EFI_{cs}, is the ethnic fragmentation index in county c and state s and is constructed as described in Section 3.

In alternative specifications, α_z is a set of county or state fixed effects to control for time-invariant unobserved heterogeneity at the county or state level. A set of time dummies to account for common trends is included in δ_t. Finally, $\mathbf{X}_c$ is a vector of county-level characteristics that correlate with the outcome of interest. This allows us to control for potential confounders including county-level demographic characteristics (i.e. population density, percentage of males, average age, poverty, percentage of adults with at least a high school degree, percentage of urban population, and percentage of population born outside of the United States) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Since the residual ε_{cst} is likely to be correlated for observations in the same state, we adjust standard errors for clustering at the state level.

The parameters λ_1 and λ_2 show the effect of federal policy and ethnic fragmentation on COVID-19 cases and deaths. The main coefficient of interest is λ_3, the coefficient of the interaction term between federal policy and the ethnic fragmentation index. This term measures how the effect of federal policy interventions is modulated by counties' levels of ethnic fragmentation.

4.2 Second Approach: Difference-in-differences Analysis

Our second methodology exploits the staggered nature of county-level mobility restriction policies to conduct a double difference design that exploits within-county variation in the main outcome of interest before and after the policy implementation across treated and untreated counties. Specifically, we estimate the following difference-in-differences specification:

$$\begin{aligned}\mathsf{Covid}_{cst} = \lambda_0 + \lambda_1 \mathsf{CountyPolicy}_{cst} + \lambda_2 \mathsf{EFI}_{cs} + \lambda_3 \mathsf{CountyPolicy}_{cst} \times \mathsf{EFI}_{cs} \\ + \alpha_z + \delta_t + \mathbf{X}_{cs}^{'} \pi + \varepsilon_{cst}\end{aligned} \tag{2}$$

Where all the regressors are defined as in the previous section save the explanatory variable $\mathsf{CountyPolicy}_{cst}$ which refers to COVID-19 related policies implemented at the county level. For each of three mobility restriction policies, the dummy variable $\mathsf{CountyPolicy}_{cst}$ equals one for dates on or after the onset of that county-level policy (in county c of state s). In our preferred specification, the variable $\mathsf{CountyPolicy}_{cst}$ is based on county-level declarations of a State of Emergency. In two other specifications we construct $\mathsf{CountyPolicy}_{cst}$ based on the implementation of non-essential business closure policies and on the implementation of safer-at-home orders.

Our key assumption is that, conditional on controls, the evolution of COVID-19 cases and fatalities for counties that implemented preventative policies would not have been different from those which did not. This is equivalent to an assumption of parallel trends in COVID-related health outcomes for treated and untreated counties.

We also implement the two identification strategies described above while replacing EFI by racial residential segregation. Moreover, we estimate the effect of EFI on COVID-19 outcomes for above-median and below-median levels of racial residential segregation to analyze how the effects of ethnic diversity on these outcomes vary with racial segregation.

4.3 Additional Robustness Checks

Finally, we conduct a number of additional robustness checks related to the above strategies. First, we analyze the dynamic effect of the interaction between ethnic fractionalization and State of Emergency declarations on COVID-19 outcomes. In another robustness check, we estimate our two main specifications using a fictitious "policy date" 45 days after the true date. Finally, we estimate an event study model to test the parallel trends assumption in our DiD model. We use an event study regression model to examine how county-level COVID-19 related health outcomes evolve during the period leading up to and following county-level mobility restrictions:

$$\begin{aligned}\mathrm{Covid}_{cst} = \lambda_0 + \sum_{t=-40}^{80} \lambda_{1(t+10)} P_{cs(t+10)} + \lambda_2 \mathrm{EFI}_{cs} + \sum_{t=-40}^{80} \lambda_3 P_{cs(t+10)} \times \mathrm{EFI}_{cs} \\ + \alpha_z + \delta_t + \mathbf{X}^{'}_{cs}\pi + \varepsilon_{cst}\end{aligned} \tag{3}$$

Where $P_{cs(t+10)}$ are dummy variables for the $t+10$ days before the policy for positive values and the $t+10$ days after the policy for negative values. The period from the beginning of data collection until thirty one days before the mobility-restricting policy is the reference period. For example, the estimated coefficients on the $P_{cs(20)}$ dummies should therefore be interpreted as the effect of being twenty days after the policy as compared to the period ending thirty one days before it.

5 Results

In this section, we summarize our estimation results. We find that while government responses have been effective in slowing the spread of COVID-19 and averting deaths, they have been much less effective in ethnically fragmented counties; this is particularly true in highly segregated areas.

5.1 Emergency Declarations, Ethnic Fragmentation, and COVID-19

We begin our analysis with a graphical illustration of the interplay between county-level emergency declarations, ethnic fragmentation, and the number of new COVID-19 cases and deaths. Figures 1-a and -b show the trends in the number of new COVID-19 cases and deaths by level of ethnic fragmentation. On the x-axis of each figure, we report the distance (in days) from the county-level State of Emergency announcement (CSOE). These graphs compare the average number of daily new COVID-19 cases (1-a) and deaths (1-b) in counties with above-median levels of the ethnic fragmentation index (highly fragmented counties) and below-median levels of the ethnic fragmentation index (relatively unfragmented counties). These graphs clearly illustrate that following the county-level Sate of Emergency declaration, the number of new COVID-19 cases and deaths increased substantially more in highly fragmented counties. These observed differences suggest an important differential effect of mobility restriction policies in counties with differing levels of ethnic fragmentation.

These results are confirmed in the regression-based analysis in Table 2. In this table we present estimates of the impact of mobility restriction policies, EFI, and their interaction on COVID-19 outcomes. The first two panels of this table display results of the pre-post analysis using the federal State of Emergency as a measure of mobility restriction policy (see equation (1)). The two panels at the bottom of the table show estimates of the difference-in-differences analysis that use the county-level State of Emergency as a measure of mobility restriction policy (see equation (2)). The outcome of interest is the cumulative number of COVID-19 cases in *Panels A* and *C*, and the cumulative number of COVID-19 deaths in *Panels B* and *D*. Estimates in column (1) show the average effects of mobility restriction policies and EFI on COVID-19 outcomes. In both the pre-post analysis and the double difference analysis, we find that ethnic fragmentation has a positive effect on COVID-19 cases and related deaths. These effects are both economically and statistically significant. In fact, moving from a county with just one ethnic group to a county that is completely fragmented along ethnic lines increases COVID-19 cases by $1,280$ and COVID-19 deaths by 75 in the pre-post estimation. These numbers are $1,932$ and 87 in the double difference analysis. Importantly, the positive association between the mobility restriction policy and COVID-19 outcomes also indicate that the number of infected individuals and deaths continued to rise following both the federal and county-level emergency declarations, suggesting that these policies might not have been uniformly effective.

In column (2), we add an interaction between our index of ethnic fragmentation and the mobility restriction policy. In *Panels A* and *B*, we find that while the effect of the policy on COVID-19 outcomes is negative, the coefficient of the interaction between mobility restriction policy and EFI is highly positive and statistically significant. Estimates in column (2) of Table 2 show that EFI marginally raised the number of COVID-19 cases (resp. deaths) by $2,030$ (resp. 119) following the federal State of Emergency declaration, and by $3,224$ (resp. 146) following the county-level State of Emergency declaration. These results mean that government responses to COVID-19 were less effective in preventing COVID-19 infections and deaths in ethnically fragmented counties. Ethnic fragmentation can therefore be seen as an important constraint on the effectiveness of quarantine measures and regulations. In column (3), we add state fixed effects to control for time-invariant state-level observed and unobserved characteristics, and day fixed effects to control for any day-specific shock common to all counties. The results remain the same. We can easily see that ethnic fragmentation continues to increase COVID-19 severity, and that federal and county-level State of Emergency policies continue to be ineffective in more ethnically fragmented counties.

In related literature, several demographic and economic factors have been linked to the spread of the pandemic. We account for these potentially confounding factors in two ways. First, in column (4), we control for a set of county-level demographic characteristics, including population density, percentage of males, average age, poverty, education, percentage of population living in urban areas, and the percentage of immigrants. We also control for county-level health characteristics, including the percentage of adults in poor health, the percentage of adults who smoke, the percentage of adults with obesity and the percentage of adults with diabetes. Adding these controls does not change the main result: both federal and county-level State of Emergency declarations remain less effective in preventing COVID-19 cases and deaths in more ethnically fragmented counties. Interestingly, the coefficient of EFI is negatively associated with COVID-19 outcomes when controlling for county-level demographic characteristics in both the pre-post and the double difference analyses (see estimates in column (4) of Table 2). This is in contrast with the positive effect in column (3) of the same table. An interpretation for these results is that the positive effect of ethnic fragmentation on COVID-19 outcomes pre-policy is likely mediated by some of the county-level socioeconomic characteristics we control for.[16] However, these same characteristics do not seem to play any significant mediating role post-policy. Our second approach to addressing confounding factors is by controlling for county and day fixed effects in column (5) (which therefore subsumes all the controls of column (4)). We find that the interaction between mobility restrictions and EFI continues to have a positive and statistically significant effect on COVID-19 outcomes, confirming that ethnic fragmentation has significantly constrained the effectiveness of both federal and county-level State of Emergency policies.

To ensure that our findings are not the results of a strong correlation between high EFI counties and the prevalence of risk factors associated with COVID-19, we assess the pairwise intersection of EFI with the demographic, economic and health factors listed above. The coefficients of correlation are reported in column (1) of Appendix Table A8. In order of importance, EFI is positively associated with immigrants, percentage of urban population, percentage of adults reporting poor health, poverty rates, population density, percentage of adults with diabetes, percentage of male population, and percentage of adults with obesity, population size, share of Trump voters.........; and it is negatively associated with the average age of the county population, level of education and the percentage of adult smokers. Reassuringly, almost all of theses variables account for less than 35% of the variance in EFI. A notable exception is for the

[16] This explanation is consistent with findings from a large literature showing that ethnic division is a cause of a broad range of social ills.

percentage of immigrants, urban population, and the average age which account for 53%, 39%, and 42% of the variance in EFI, respectively. In addition, we regress EFI on COVID-19 related risk factors and collected the residual from the regression to find that the latter accounts for a large amount (73%) of the variance in EFI. The correlation between the residual and EFI is slightly stronger when we use the residual from a fitted regression between EFI and the three most important risk factors defined using a Principal Component Analysis (PCA). These results imply that our estimates are not driven by prevalence of COVID-19 related risk factors in high EFI counties.

For robustness, we consider an alternative measure of the federal policy response to COVID-19. Using the pre-post analysis specification in equation (1), we replace the timing of the federal State of Emergency announcement with an index measuring the degree of stringency of the federal policy response to COVID-19 (see description in Section 3). Results are reported in *Panels A* and *B* of Table 3. In these panels we replicate the same analysis as in the top two panels of Table 2, but this time measuring mobility restriction using the stringency index. Consistent with the results in Table 2 we find that government responses to COVID-19 were more effective at reducing COVID-19 infections and deaths in less ethnically fragmented counties.

County governments implemented several other mobility restriction measures to reduce COVID-19 infections. For instance, governments declared safer-at-home orders and business closures. In a second sensitivity analysis, we assess the interplay between the announcement of these alternative mobility restriction measures and the ethnic fragmentation index. Results are summarized in *Panels C-F* of Table 3. Our main conclusion that mobility restriction policies were less effective at reducing COVID-19 cases and deaths in more ethnically fragmented counties remain the same. When we consider alternative mobility restriction policies including safer-at-home orders and business closures, the findings are qualitatively similar and the magnitude of the effect is stronger (see *Panels C-F* of Table 5).

In the results of Tables 2 and 3, the dependent variables are the absolute number of COVID-19 cases and deaths. We replicate the analysis in Appendix Tables B1 and B2 using the rates of COVID-19 cases and deaths instead as the dependent variables. In executing this analysis, we remove population size from the set of controls. Our main conclusions are intact. In columns (2)-(5) of *Panels A-D* of Appendix Table B1), the coefficient of the interaction between mobility restriction policy and EFI is highly positive and statistically significant. Estimates from our most conservative specification (column (5)) show that EFI marginally raised the number of COVID-19 cases (resp. deaths) by around 416 (resp. 18) per 100,000 inhabitants following the federal State of Emergency declaration, and by around 344 (resp. 16) per 100,000 inhabitants following the county-level State of Emergency declaration. The findings are qualitatively the same when we consider other measures of mobility restrictive policies (Appendix Table B2). These results confirm that that government responses to COVID-19 were less effective in preventing COVID-19 infections and deaths in ethnically fragmented counties.

We next study the dynamics of the effect of mobility-restricting policies' interactions with ethnic fragmentation. To do so, we consider different bandwidths around the date of the federal and county-level State of Emergency declarations. The estimated coefficients of the interaction terms between the federal State of Emergency and EFI, and the county-level State of Emergency and EFI are represented under increasingly large bandwidths in Figure 4. We find that the ineffectiveness of federal and county-level mobility restrictions in averting new COVID-19 cases and deaths in more ethnically fragmented counties increases over time. These results indicate that mobility restriction policies generated sharp and increasing inequalities in COVID-19 outcomes between ethnically fragmented counties and those that are more homogeneous.

As discussed in Section 4), our difference-in-differences methodology assumes parallel trends in the outcome of interest between treated and control groups in the pre-policy period. To consider potential violation of common trends, we conduct an event-study analysis of COVID-19 cases and deaths. The results are reported in Figure 5. We find no statistically significant evidence of a differential effect of mobility restriction policies in highly fragmented counties during the days prior to the county-level State of Emergency declaration. Each point estimate is also near zero. Following the policy date, the estimated effect of the interaction between county State of Emergency and EFI on COVID-19 cases and deaths increases, becoming largest after 80 days following the emergency declaration. These findings are consistent with a causal interpretation of our findings in Tables 2 and 3.

We further validate our results by conducting an in-time placebo test. We create a fictitious policy 45 days after the true emergency declaration date, whether at the federal or county level. The estimates of the effect of the interaction between the fictitious date of the State of Emergency declaration and EFI are reported in Figure 6 for different bandwidths around this date. We do not find any significant differential effect of mobility restrictions on COVID-19 cases or deaths in more ethnically fragmented areas. The estimates are small and statistically indistinguishable from zero for both the federal and county emergency declarations, for all bandwidths. This clearly contrasts with the results displayed in Figure 4 showing the dynamics of these effects under the true policy date.

5.2 Emergency Declarations, Racial Segregation, and COVID-19

We now document the effect of racial residential segregation, mobility restriction policies, and their joint impact on COVID-19 outcomes. Similar to Figures 1-a and 1-b, Figures 2-a and 2-b plot the trends in the average number of new daily COVID-19 cases and deaths in counties with above-median levels of racial segregation and counties with below-median levels of racial segregation for the days before and after the county-level State of Emergency declaration. What clearly emerges is that following the federal and county-level State of Emergency declarations, there is a substantial increase in the number of new COVID-19 cases and deaths in more segregated counties, suggesting that federal State of Emergency and county-level State of Emergency policies are significantly less effective in reducing the spread of COVID-19 in counties with a high level of racial segregation. Regression analyses in Table 4 underscore the magnitude of these effects.

In Table 4, *Panels A* and *B* replicate the pre-post analysis in Table 2, while *Panels C* and *D* replicate the difference-in-differences analysis from the same table, this time replacing ethnic fragmentation with white-vs-non-white residential segregation as defined in Section 3.[17] The first column presents the average effects of the mobility restriction policy and racial segregation. We find that racial segregation positively affects both COVID-19 cases and deaths. Moving from a county with no racial segregation to a county that is completely segregated increases COVID-19 cases by $1,400$ and COVID-19 deaths by 89 when we control for the federal State of Emergency declaration (see *Panels A* and *B*). These outcomes are $2,017$ and 102, respectively, when we control for the county-level State of Emergency declaration (see *Panels C* and *D*).

In column (2), we add an interaction between the index of racial residential segregation and the mobility restriction policy. We find that the effect of the policy on COVID-19 outcomes is negative while the coefficient of the interaction term is significantly positive. This is the case regardless of whether we consider the federal policy (*Panels A* and *B*) or the county-level policy (*Panels C* and *D*). These findings imply that mobility restriction measures were effective in counties displaying low levels of racial segregation, but were ineffective in highly segregated counties. Following President Trump's State of Emergency declaration, moving from a county with no racial segregation to a county with the highest level of racial segregation increased COVID-19 cases and associated deaths by $2,221$ and 141, respectively. Similarly, following the county-level State of Emergency declaration, moving from a county with no racial segregation to a county with the highest level of racial segregation increased COVID-19 cases and associated deaths by $3,412$ and 173, respectively.[18] As shown in columns (3), (4), and (5), these results are not driven by time-invariant state and/or county level determinants of COVID-19 outcomes. The latter conclusion that our results in Table 4 are not driven by risk factors relevant for COVID-19 outcomes is confirmed in column (3) of Appendix Table A9. In this table, we replicate the analysis in column (1) but this time replacing EFI with the white-non-white residential segregation index. Using the residual from a fitted regression between racial residential segregation index and COVID-19 related risk factors, we find that 96% of the variance in the residential segregation index is explained by the residual, which implies that estimates in Table 4 are not driven by the prevalence of COVID-19 related risk factors in highly segregated counties. These results are also robust to alternative specifications. In particular, we replicate the analysis in Table 4 using other mobility restriction policies and find similar results that mobility restrictions to reduce COVID-19 cases and deaths are less effective in highly segregated counties (see Table 5). In Appendix Table A1, we conduct a similar robustness check by considering an index of residential segregation between black and white county residents and reach the same conclusion.

For additional robustness checks, we replicate the analysis of Tables 4 and 5, with the rates of

[17] In the Appendix, we find similar results when using an index of residential segregation between white and black county residents (Appendix Table A1).

[18] By construction, the value of the segregation index is 0 in a county with no racial segregation and 100 in a county with the highest level of racial segregation. These estimates are therefore obtained by multiplying the regression coefficients by 100.

COVID-19 cases and deaths as the dependent variables. The findings are reported in Appendix Tables B3 and B4. We remove population size from the set of controls. Our main conclusions are unchanged. In columns (2)-(5) of *Panels A-D* of Appendix Table B3), the coefficient of the interaction between mobility restriction policy and the white-vs-non-white segregation index is positive and statistically significant. Estimates from our most conservative specification (column (5)) show that following President Trump's state of Emergency declaration, moving a county with no racial segregation to a county with complete segregation increased COVID-19 cases and deaths by 307 and 17 per $100,000$ inhabitants, respectively. Similarly, following the county-level State of Emergency declaration, moving from a county with no racial segregation to a county with complete racial segregation increased COVID-19 cases and associated deaths by 268 and 13, respectively. The findings are qualitatively similar when we consider alternative measures of mobility restrictive policies (Appendix Table B4). These results confirm that that government responses to COVID-19 were less effective in preventing COVID-19 infections and deaths in racially segregated counties.

5.3 Diversity with(out) Divisions: When Does Ethnic Fragmentation Matter?

We argue that ethnic division, rather than ethnic diversity, is driving the ineffectiveness of mobility-restricting policies in the United States. This is because the mechanisms by which ethnicity could matter for communicable disease transmission matter only if ethnicity represents a barrier to interaction between groups. While ethnic heterogeneity and ethic division have been considered, at least empirically, to be commensurate in economics, we emphasize the role of measured residential segregation in capturing ethnic divisions. Ethnic diversity and racial segregation are only weakly correlated in United States cities (Uslaner (2010)), as also confirmed in our dataset. By examining the interaction between diversity (EFI) and racial divisions (racial residential segregation), we find that the negative impact of EFI on the efficacy of mobility-restricting policies only exists where both diversity and divisions are present. Our paper contributes to a small literature which explores the role of both segregation and diversity for economic outcomes. For example, Beach and Jones's (2017) finding that public good provision is lower in U.S. cities with more diverse city councils is driven by cities with high segregation. In a study of neighborhood diversity in England, Fumagalli and Fumagalli (2019) find that while neighborhood diversity increases purposeful activity among adolescents, neighborhood ethnic segregation decreases it. Uslaner (2012) presents correlational evidence from several countries; he finds that integrated diverse neighborhoods display high levels of trust while diverse neighborhoods with high levels of residential segregation display low levels of trust.

Figure 7 and Appendix Table A7 summarize the effects of EFI on the effectiveness of mobility restriction policies, disaggregating by decile of racial residential segregation. For each decile of residential segregation, *Panel A* of Figure 7 reports the coefficient of a regression of cases of COVID-19 on an interaction of EFI and the federal State of Emergency declaration (in blue), and the coefficient of a regression of cases of COVID-19 on interaction between EFI and CSOE (in red). Both regression specifications include controls for: county-level characteristics (i.e. total population, population density, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters), and county-level health characteristics (i.e. the percentage of adults with obesity, "poor health", diabetes, and who smoke), the interacted measures separately, as well as for state and day fixed effects. *Panel B* of Figure 7 reports the same information for deaths associated with COVID-19. Coefficient estimates suggest that EFI has a non-positive effect on the efficacy of both the federal State of Emergency declaration and on county-level State of Emergency declarations. However, when white-vs-non-white residential segregation is in the lowest decile, the marginal effect of EFI on the effectiveness of mobility restriction policies is quite small (an increase of 49 cases and of less than 2 death). As the decile of residential segregation increases, the negative impact of EFI on mobility restriction policies increases as well. Within the highest decile of residential segregation, there were $3,726$ more cases of COVID-19 and 270 more deaths in counties in the highest quintile of EFI than in counties in the lowest quintile following the federal declaration. Following the institution of county-level State of Emergencies, within the most segregated counties, there were $4,057$ more cases of COVID-19 and 212 more deaths in counties in the highest quintile of EFI than in those in the lowest quintile.[19] These numbers are not surprising given the marginal effects of the interaction between EFI and the highest decile of racial segregation ($9,661$ and 515, respectively).

The regression analysis in Table 6 further illustrates the importance of residential segregation in explaining the role of EFI on the efficacy of mobility restriction policies. *Panels A* and *B* of this table summarize the effects of EFI, the federal State of Emergency declaration, and their interaction on the number of COVID-19 cases and deaths separately for counties with below-median and above-median levels of residential segregation. Following the emergency declaration, the marginal effect of EFI in counties with high levels of residential segregation is roughly eight times the marginal effect of EFI in counties with low residential segregation across all specifications. In our preferred specification (shown in columns 3 and 4), within highly segregated counties, moving from the lowest EFI areas to the highest EFI areas is associated with a statistically significant increase of $4,197$ cases following the federal State of Emergency declaration, and by an increase of only 331 cases within low-segregation counties. Following the federal declaration, there were 255 more deaths in the highest EFI areas than in the lowest EFI areas in counties of high residential segregation and an increase of 11 more deaths in low-segregation areas.

This pattern — that preventative policies are drastically less effective in areas of high-segregation relative to areas of low-segregation — holds for COVID-19 cases and deaths following the institution of county-level State of Emergency policies as well. Living in a county with the highest level of ethnic fragmentation rather than in a county with the lowest level of ethnic fragmentation within the set of high-segregation counties following county-level State of

[19]These numbers are computed using estimates in Appendix Table A7

Emergency is associated with an increase of 5,336 additional cases and 248 additional deaths compared to only 778 additional cases and 28 additional deaths in a low-segregation counties. These results remain the same when using alternative measures of mobility restrictions as we can see from estimates in Table 7. Also, the findings presented in this section do not change qualitatively when we consider an index of residential segregation between white and black county residents (see Appendix Tables A3 and A4).

We also conduct the analysis using the rates of COVID-19 cases and deaths as the dependent variables. We replicate Figure 7, Appendix Table A7, and Tables 6 and 7. We exclude county population from the set of controls. The corresponding results are presented in Figure 8 and Appendix Tables B7, B5, B6, respectively. Our main conclusions do not differ from those obtained from analyzing the absolute number of COVID-19 cases and deaths. Figure 8 shows that when white-non-white residential segregation is in the lowest decile, the marginal effect of EFI on the effectiveness of mobility restriction policies is close to zero. The negative effect of EFI on the impact of mobility restriction policies increases with racial segregation. In the highest decile of racial segregation, EFI marginally increases the number of COVID-19 cases and deaths by 342 and 19 per 100,0000 inhabitants respectively following President Trump's State of Emergency declaration, and by 355 and 17 per 100,000 inhabitants respectively following the county's State of Emergency declaration. In Appendix Table B5, we analyze how EFI affects the efficacy of mobility restriction policies in counties with below-median and above-median levels of residential segregation. In counties with below-median levels of residential segregation, EFI marginally increased COVID-19 cases and deaths by around 314 and 10 per 100,000 inhabitants respectively following President Trump's State of Emergency declaration, versus around 558 and 28 per 100,000 inhabitants respectively in counties with above-median levels of residential segregation. Similarly, following the county's State of Emergency declaration, EFI marginally increased COVID-19 cases and deaths by 282 and 12 per 100,000 inhabitants respectively in counties with below-median levels of residential segregation, versus 397 and 19 per 100,000 inhabitants respectively in counties with above-median levels of residential segregation. The findings do not change qualitatively when we consider alternative measures of mobility restriction policies (Appendix Table B6). These findings confirm that preventative policies are drastically less effective in areas of high-segregation relative to areas of low-segregation.

6 Mechanisms

In this section, we document possible mechanisms through which ethnic divisions may have reduced the effectiveness of containment policies. First, we analyze how ethnic divisions matter for self-quarantining. We next describe the relationship between ethnic divisions and the use of masks following the implementation of mobility-restricting policies. Finally, we provide evidence that ethnic divisions reduce the prevalence of membership associations potentially rendering communication more sparse, prosocial norms weaker, and the ability of communities to enact social sanctions reduced.

6.1 Mobility Evidence of Restriction Policies' Efficacy

We have shown that ethnic fragmentation has negatively impacted the number of COVID-19 cases and deaths, and has reduced the efficacy of public policies aimed at mitigating these negative outcomes. The negative role played by ethnic fragmentation is heightened in areas that are more racially segregated. In this section we provide direct evidence of lockdown policies' decreased effectiveness in ethnically divided counties — the mobility impacts of State of Emergency declarations. We explore multiple mobility variables which measure change in visits to: (1) retailers and recreational outlets; (2) groceries and pharmacies; (3) parks; (4) transit stations; (5) work places; and (6) residences. Time spent at some locations was directly impacted by lockdown policies which closed physical businesses (i.e. retail and recreation, workplaces), while others remained open under emergency declarations (i.e. groceries, pharmacies, parks, transit). While mobility changes in the former set of locations may reflect the stringency of local legislation, mobility changes in the latter set of locations represent voluntary changes in response to COVID-19 risk. Examining mobility in these locations provides a measure of voluntary personal and prosocial risk reduction.

Our mobility variables are adjusted for COVID-19 cases and deaths. Indeed, while an individual might change their mobility behavior in response to mobility restriction policies, behavioral change is also likely to be endogenous to COVID-19 prevalence in their neighborhood. We account for this endogeneity by computing the ratio of a given mobility variable at time t to the accumulated number of COVID-19 cases at time t. We then estimate the effects of policies on the variables thus generated and analyze how these effects vary by level of ethnic divisions.

A graphical description of the findings is presented in Figure 9. This figure shows that county-level emergency declarations were successful at increasing self-quarantining. Mobility levels dropped following emergency declarations, but mobility in certain categories including visits to workplaces, transit stations, and retail and recreational outlets increased soon thereafter (though not reaching pre-emergency declaration levels in general). In addition, the efficacy of the emergency declaration was higher in counties where ethnic fragmentation is low. Prior to the declaration, counties with low and high levels of ethnic fragmentation had similar mobility levels. Following the emergency declaration, mobility dropped more in counties with low levels of ethnic fragmentation.

We confirm these descriptive findings in a regression-based framework. We estimate equations (1) and (2), where the dependent variable is any of the aforementioned mobility variables. As in Section 5, we consider both national and county-level State of Emergency policies. Our results are presented in Tables 8-11. In Table 8, we analyze the effect of the national emergency declaration on different categories of mobility. We find that the national emergency declaration increases visits to residences (column (1) of Panel F) and decreases all of the other categories of mobility (column (1) of Panels A-E). However, the efficacy of this policy at reducing mobility is much lower in counties with higher levels of ethnic fragmentation. Indeed, the effect of the interaction term between the national emergency declaration and ethnic fragmentation is positive for all categories of mobility (columns (2)-(5) of Panels A-E) except visits to residential places for which the effect is negative (columns (2)-(5) of Panel F). When we consider county-level emergency declarations (Table 9), the findings are qualitatively similar and the effects are stronger in magnitude and statistical significance.

In Table 10, we analyze the interacting effect of the national emergency declaration and ethnic fragmentation by level of residential segregation. We find that this effect is much higher in highly segregated counties, except when the outcome variables are visits to groceries and pharmacies and visits to parks. In general, these findings imply that the efficacy of policies aimed at curbing the spread of COVID-19 is even much lower for more ethnically fragmented counties that are also more racially segregated. The findings are qualitatively similar, for some outcomes, when we consider county-level emergency declarations (Table 11). In addition, in Appendix Tables A5 and A6, we find qualitatively similar results when using an index of residential segregation between white and black county residents.

6.2 Mask-wearing and Ethnic Divisions

In addition to reduced mobility and physical distancing, the use of masks to cover the mouth and nose has been prescribed by health organizations and governments around the world as a way to limit the spread of COVID-19. Due to its health externalities, the use of masks can be considered a contribution to a public good. In this section, we analyze how ethnic divisions have impacted the adoption of this behavior in U.S. counties.

Our data on mask-wearing come from county-level estimates released by the New York Times, and are available only for the month of July 2020. This variable is measured at the county level and represents the proportion of individuals who use a mask to cover their face when they are outside of the home. Because these data were only collected after most mobility-restricting measures were in place, we cannot analyze how these policies affected face covering. However, we believe that observing the correlation between face covering and ethnic divisions is likely to shed additional light on how the latter have reduced the efficacy of preventative policies.

We regress mask-wearing on EFI and on residential segregation (Table 12). All specifications include state fixed effects. The estimate reported in column (1) implies that people living in the highest EFI counties are 7 percentage points less likely to report "frequently" wearing a mask than are people living in the lowest EFI counties. In column (2), mask-wearing is regressed only on black-white residential segregation. The estimate implies that living in a county with the highest level of racial segregation rather than a county with the lowest level of racial segregation decreases the frequent use of masks by 0.9 percentage points. Column (3) includes controls for both variables. We note that the effect of EFI decreases while that of black-white segregation increases. The reduction in the effect of EFI can be explained by the drop of observations for which the value of black-white segregation is not available. In column (4), we regress mask-wearing on the index of segregation between whites and others, uncovering an effect that is larger (-3.7 percentage points) than that of black-white segregation. When both EFI and the index of segregation between whites and others are controlled in column (5), we see that each has a negative and significant effect on mask-wearing. Overall, these findings show that ethnic divisions discouraged mask-wearing during the COVID-19 pandemic, which provides another channel through which they might have weakened the effectiveness of preventative policies in more ethnically divided counties of the United States.

6.3 Membership Associations and Ethnic Divisions

In this section, we provide some evidence that ethnic divisions reduce social association rates, which potentially renders communication more sparse and prosocial norms weaker, reducing the ability of communities to enact social sanctions. Indeed, the ability of communities to enforce policies critically depends on how internally cohesive and well-integrated they are. Social cohesion facilitates communication and makes it easier to define common rules and expectations during a pandemic like COVID-19. Better communication can also facilitate the implementation of preventative policies like contact tracing.

We analyze how the effect of EFI on social association rates–measured as the number of membership associations per $10,000$ individuals in a county– varies by level of racial segregation. Data on social association rates are obtained from 2017 County Health Rankings, the most recent year for which data are available. We regress social association rate on EFI for each decile of white-vs-non-white and black-white residential segregation, and report the estimates in Figures 10-*a* and 10-*b* and Appendix Table A8. We find that ethnic fragmentation decreases social association, but that this negative effect is driven by racial segregation. When the level of racial segregation is low, EFI has no statistically significant effect on social association, but its effect is larger and statistically significant in areas with sufficiently high levels of racial segregation. Living in a county with a one standard deviation higher level of EFI is associated with an increase of 0.10 membership associations per $10,000$ in counties in the first decile of racial segregation, and is associated with a 1.25 per $10,000$ decrease in the number of membership associations within the tenth decile of black-white segregation. The results are qualitatively similar for white-vs-non-white segregation, but they are less statistically significant.

These results are consistent with the earlier reported findings that the reduced effectiveness of mobility-restricting policies associated with ethnic fragmentation is almost entirely driven by racial residential segregation. Altogether, our analysis suggests that ethnic fragmentation weakened mobility restriction measures *only in areas where interracial interactions and social associations are absent.* Ethnic fragmentation in the absence of racial divisions does not appear to be harmful.

7 Conclusion

There has been little attention given to how ethnic composition matters for the efficacy of, and adherence to, policy measures implemented in response to crises. In particular, it is difficult to disentangle the role played by *ethnic divisions* from role played by *ethnic diversity.* This constitutes a significant constraint on policy design in multiethnic societies. Using the lens of the COVID-19 pandemic in the United States, we present causal evidence on the distinct and joint effects of ethnic divisions and ethnic diversity on the efficacy of government policies designed to address this crisis.

We find that while areas with high levels of ethnic diversity fared worse in both COVID-19 cases and deaths after federal and county-level State of Emergency declarations, these effects are driven by the response of counties with high levels of racial residential segregation — a one standard deviation higher level of ethnic fragmentation is associated with nearly *seven times more cases* of COVID-19 and *ten times more deaths* in highly segregated counties than in more integrated counties. In areas with high levels of ethnic divisions, there were smaller mobility reductions in response to federal and county-level policies. Despite higher disease prevalence, residents of these areas were less likely to report frequently wearing a mask.

Our analysis therefore suggests that in crises in which externalities play an important role, ethnicity matters only inasmuch as it presents a barrier to interactions between groups. Ethnic division, rather than ethnic diversity, forms such a barrier. Where group divisions exist, communication is sparser, pro-social norms are weaker, and communities are less able to enforce government programs (e.g., mobility restrictions) by enacting social sanctions. These group divisions are particularly problematic in the United States which has, to date, been unable to enact rigorous formal enforcement against violations of COVID-19 related policies. Further, the delegation of pandemic management to states and localities has meant that local group divisions which might hinder policy production, pro-sociality, and public goods provision have had an outsized impact on the effect of preventative policies. From a policy perspective, all of our proposed mechanisms suggest that federal policy making and enforcement, which can circumvent local coordination problems, could be a good approach to ensure that best practices are followed. Our analysis also suggests that policies which promote ethnic and racial integration can ameliorate the efficacy of government response to, and allay the negative social and economic impacts of, crises characterized by wide-scale externalities.

References

Alesina, A., Baqir, R., & Easterly, W. (1999). Public goods and ethnic divisions. *The Quarterly Journal of Economics*, *114*(4), 1243–1284.

Alesina, A., & Ferrara, E. L. (2005). Ethnic diversity and economic performance. *Journal of Economic Literature*, *43*(3), 762–800.

Alesina, A., Gennaioli, C., & Lovo, S. (2019). Public goods and ethnic diversity: Evidence from deforestation in indonesia. *Economica*, *86*(341), 32–66.

Alesina, A., & La Ferrara, E. (2000). Participation in heterogeneous communities. *The Quarterly Journal of Economics*, *115*(3), 847–904.

Alesina, A., & Zhuravskaya, E. (2011). Segregation and the quality of government in a cross section of countries. *American Economic Review*, *101*(5), 1872–1911.

Algan, Y., Hémet, C., & Laitin, D. D. (2016). The social effects of ethnic diversity at the local level: A natural experiment with exogenous residential allocation. *Journal of Political Economy*, *124*(3), 696–733.

Andrasfay, T., & Goldman, N. (2021, February). Reductions in 2020 US life expectancy due to COVID-19 and the disproportionate impact on the Black and Latino populations. *Proceedings of the National Academy of Sciences*, *118*(5). (Publisher: National Academy of Sciences Section: Social Sciences)

Balliet, D. (2010). Communication and cooperation in social dilemmas: A meta-analytic review. *Journal of Conflict Resolution*, *54*(1), 39–57.

Barrios, J. M., Benmelech, E., Hochberg, Y. V., Sapienza, P., & Zingales, L. (2021, January). Civic capital and social distancing during the Covid-19 pandemic. *Journal of Public Economics*, *193*, 104310.

Baum-Snow, N., & Lutz, B. F. (2011). School desegregation, school choice, and changes in residential location patterns by race. *American Economic Review*, *101*(7), 3019–46.

Bazzi, S., Gaduh, A., Rothenberg, A. D., & Wong, M. (2019). Unity in diversity? how intergroup contact can foster nation building. *American Economic Review*, *109*(11), 3978–4025.

Beach, B., & Jones, D. B. (2017). Gridlock: Ethnic diversity in government and the provision of public goods. *American Economic Journal: Economic Policy*, *9*(1), 112–36.

Blau, P. M. (1964). *Exchange and Power in Social Life.* Transaction Publishers.

Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., … others (2020). Economic and social consequences of human mobility restrictions under covid-19. *Proceedings of the National Academy of Sciences*, *117*(27), 15530–15535.

Boustan, L. P. (2010). Was postwar suburbanization âwhite flightâ? evidence from the black migration. *The Quarterly Journal of Economics*, *125*(1), 417–443.

Boustan, L. P. (2012). Racial residential segregation in american cities. *In. Brooks, N., Donaghy, K., Knaap, G-J (eds) The Oxford handbook of urban economics and planning*, Oxford University Press.

Brooks, N., Donaghy, K., & Knaap, G.-J. (2012). *The oxford handbook of urban economics and planning*. Oxford University Press.

Card, D., Mas, A., & Rothstein, J. (2008). Tipping and the dynamics of segregation. *The Quarterly Journal of Economics*, *123*(1), 177–218.

Card, D., & Rothstein, J. (2007). Racial segregation and the black–white test score gap. *Journal of Public Economics*, *91*(11-12), 2158–2184.

Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The Quarterly Journal of Economics*, *129*(4), 1553–1623.

Cutler, D. M., & Glaeser, E. L. (1997). Are ghettos good or bad? *The Quarterly Journal of Economics*, *112*(3), 827–872.

Desmet, K., Ortuño-Ortín, I., & Wacziarg, R. (2017). Culture, ethnicity, and diversity. *American Economic Review*, *107*(9), 2479–2513.

Dincer, O. C. (2011). Ethnic diversity and trust. *Contemporary Economic Policy*, *29*(2), 284–293.

Ding, W., Levine, R., Lin, C., & Xie, W. (2020, June). *Social Distancing and Social Capital: Why U.S. Counties Respond Differently to COVID-19* (Tech. Rep. No. w27393). National Bureau of Economic Research.

Duncan, O. D., & Duncan, B. (1955). A methodological analysis of segregation indexes. *American Sociological Review*, *20*(2), 210–217.

Durante, R., Guiso, L., & Gulino, G. (2020). Asocial capital: Civic culture and social distancing during covid-19. *Journal of Public Economics*, *194*, 104342.

Easterly, W., & Levine, R. (1997). Africa's growth tragedy: policies and ethnic divisions. *The Quarterly Journal of Economics*, *112*(4), 1203–1250.

Ejdemyr, S., Kramon, E., & Robinson, A. L. (2018). Segregation, ethnic favoritism, and the strategic targeting of local public goods. *Comparative Political Studies*, *51*(9), 1111–1143.

Ellingsen, T., & Östling, R. (2010). When does communication improve coordination? *American Economic Review*, *100*(4), 1695–1724.

Eric Oliver, J., & Wong, J. (2003). Intergroup prejudice in multiethnic settings. *American Journal of Political Science*, *47*(4), 567–582.

Fafchamps, M. (2000). Ethnicity and credit in african manufacturing. *Journal of Development Economics*, *61*(1), 205–235.

Finseraas, H., Hanson, T., Johnsen, Å. A., Kotsadam, A., & Torsvik, G. (2019). Trust, ethnic diversity, and personal contact: A field experiment. *Journal of Public Economics*, *173*, 72–84.

Fong, C. M., & Luttmer, E. F. (2009). What determines giving to hurricane katrina victims? experimental evidence on racial group loyalty. *American Economic Journal: Applied Economics*, *1*(2), 64–87.

Fumagalli, E., & Fumagalli, L. (2019). Neighbourhood ethnic composition and social participation of young people in england. *The Economic Journal*, *129*(622), 2459–2521.

Graham, B. S. (2018). Identifying and estimating neighborhood effects. *Journal of Economic Literature*, *56*(2), 450–500.

Guryan, J. (2004). Desegregation and black dropout rates. *American Economic Review*, *94*(4), 919–943.

Hale, T., Petherick, A., Phillips, T., & Webster, S. (2020). Variation in government responses to covid-19. *Blavatnik School of Government Working Paper*, *31*.

Hanson, A., & Hawley, Z. (2011). Do landlords discriminate in the rental housing market? evidence from an internet field experiment in us cities. *Journal of urban Economics*, *70*(2-3), 99–114.

Horowitz, D. L. (1993). The challenge of ethnic conflict: democracy in divided societies. *Journal of democracy*, *4*(4), 18–38.

Iceland, J., Weinberg, D. H., & Steinmetz, E. (2002). Racial and ethnic residential segregation in the united states: 1980-2000. In *Census 2000 Special Reports* (p. 151). Washington, DC: U.S. Government Printing Office.

Kandori, M. (1992). Social norms and community enforcement. *The Review of Economic Studies*, *59*(1), 63–80.

Kolata, G. (2020, December). Social Inequities Explain Racial Gaps in Pandemic, Studies Find. *The New York Times*. Retrieved 2020-12-11, from https://www.nytimes.com/2020/12/09/health/coronavirus-black-hispanic.html

Kreps, D. M., & Wilson, R. (1982). Reputation and imperfect information. *Journal of Economic Theory*, *27*(2), 253–279.

Leibbrandt, A., & Sääksvuori, L. (2012). Communication in intergroup conflicts. *European Economic Review*, *56*(6), 1136–1147.

Lindqvist, E., & Östling, R. (2013). Identity and redistribution. *Public Choice*, *155*(3-4), 469–491.

Luttmer, E. F. (2001). Group loyalty and the taste for redistribution. *Journal of political Economy*, *109*(3), 500–528.

Maskin, E., Fudenberg, D., & Levine, D. (1994). The folk theorem with imperfect public information. *Econometrica*, *62*(5).

Massey, D. S., & Denton, N. A. (1988). The dimensions of residential segregation. *Social Forces*, *67*(2), 281–315.

Mauro, P. (1995). Corruption and growth. *The Quarterly Journal of Economics*, *110*(3), 681–712.

Miguel, E. (2004, April). Tribe or Nation? Nation Building and Public Goods in Kenya versus Tanzania. *World Politics*, *56*(3), 327–362. (Publisher: Cambridge University Press)

Miguel, E., & Gugerty, M. K. (2005). Ethnic diversity, social sanctions, and public goods in kenya. *Journal of Public Economics*, *89*(11-12), 2325–2368.

Mouw, T., & Entwisle, B. (2006). Residential segregation and interracial friendship in schools. *American Journal of Sociology*, *112*(2), 394–441.

Müller, S., & Rau, H. A. (2020). Economic preferences and compliance in the social stress test of the covid-19 crisis. *Journal of Public Economics*, 104322.

Ostrom, E., & Walker, J. (1991). Communication in a commons: cooperation without external enforcement. *Laboratory Research in Political Economy*, 287–322.

Ostrom, E., Walker, J., & Gardner, R. (1992). Covenants with and without a sword: Self-governance is possible. *American Political Science Review*, *86*(2), 404–417.

Page, M. (1995). Racial and ethnic discrimination in urban housing markets: Evidence from a recent audit study. *Journal of Urban Economics*, *38*(2), 183–206.

Peterson, R. D., & Krivo, L. J. (2009). Segregated spatial locations, race-ethnic composition, and neighborhood violent crime. *The Annals of the American Academy of Political and Social Science*, *623*(1), 93–107.

Pongou, R. (2009). Anonymity and infidelity: Ethnic identity, strategic cross-ethnic sexual network formation, and hiv/aids in africa. *Unpublished Paper, Department of Economics, Brown University*.

Pongou, R., Tchuente, G., & Tondji, J.-B. (2020). *An economic model of health-vs-wealth prioritization during covid-19: Optimal lockdown, network centrality, and segregation* (Tech. Rep.). National Institute of Economic and Social Research.

Rose, A. M. (1966). Review of negroes in cities: Residential segregation and neighborhood change. *Political Science Quarterly*, *81*(2), 346–348. (Publisher: [Academy of Political Science, Wiley])

Rothwell, J. T. (2012). The effects of racial segregation on trust and volunteering in us cities. *Urban Studies*, *49*(10), 2109–2136.

Sigelman, L., Bledsoe, T., Welch, S., & Combs, M. W. (1996). Making contact? black-white social interaction in an urban setting. *American Journal of Sociology*, *101*(5), 1306–1332.

Sparber, C. (2008). A theory of racial diversity, segregation, and productivity. *Journal of Development Economics*, *87*(2), 210–226.

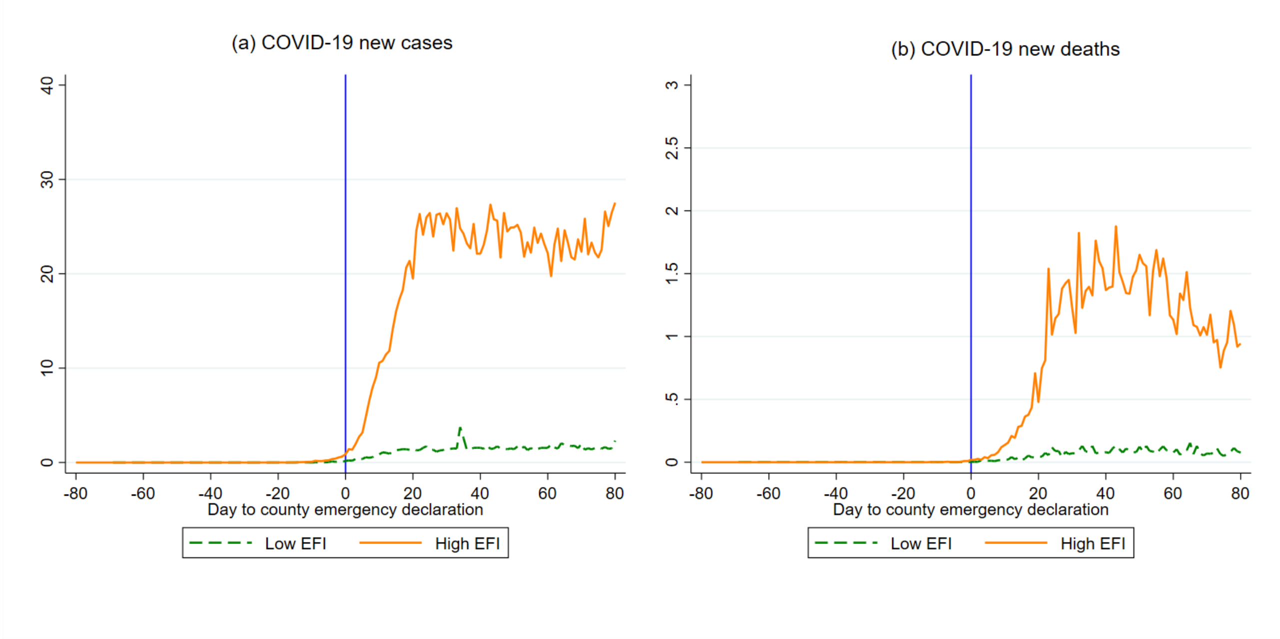
Uslaner, E. M. (2010). Segregation, mistrust and minorities. *Ethnicities*, *10*(4), 415–434.

Uslaner, E. M. (2012). *Segregation and mistrust: Diversity, isolation, and social cohesion.* Cambridge University Press.

Yan, Y., Malik, A. A., Bayham, J., Fenichel, E. P., Couzens, C., & Omer, S. B. (2020). Measuring voluntary social distancing behavior during the covid-19 pandemic. *MedRxiv*.

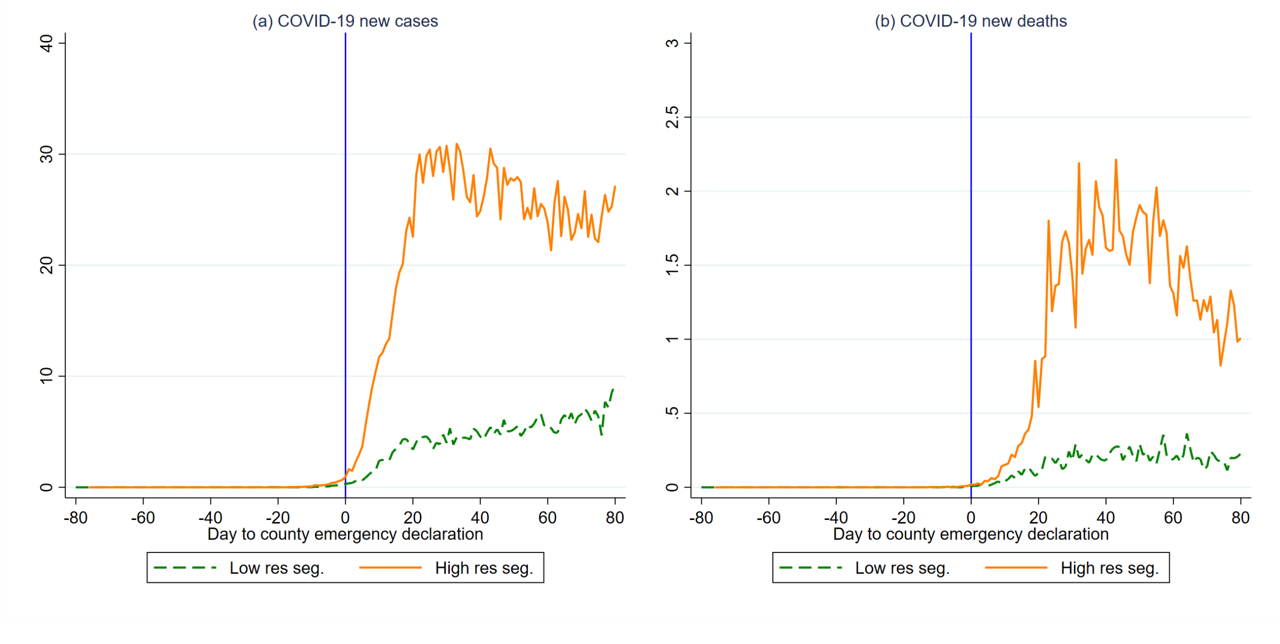
Zingher, J. N., & Steen Thomas, M. (2014). The spatial and demographic determinants of racial threat. *Social Science Quarterly*, *95*(4), 1137–1154.

Figure 1: COVID-19 and county-level emergency declaration by level of ethnic fragmentation



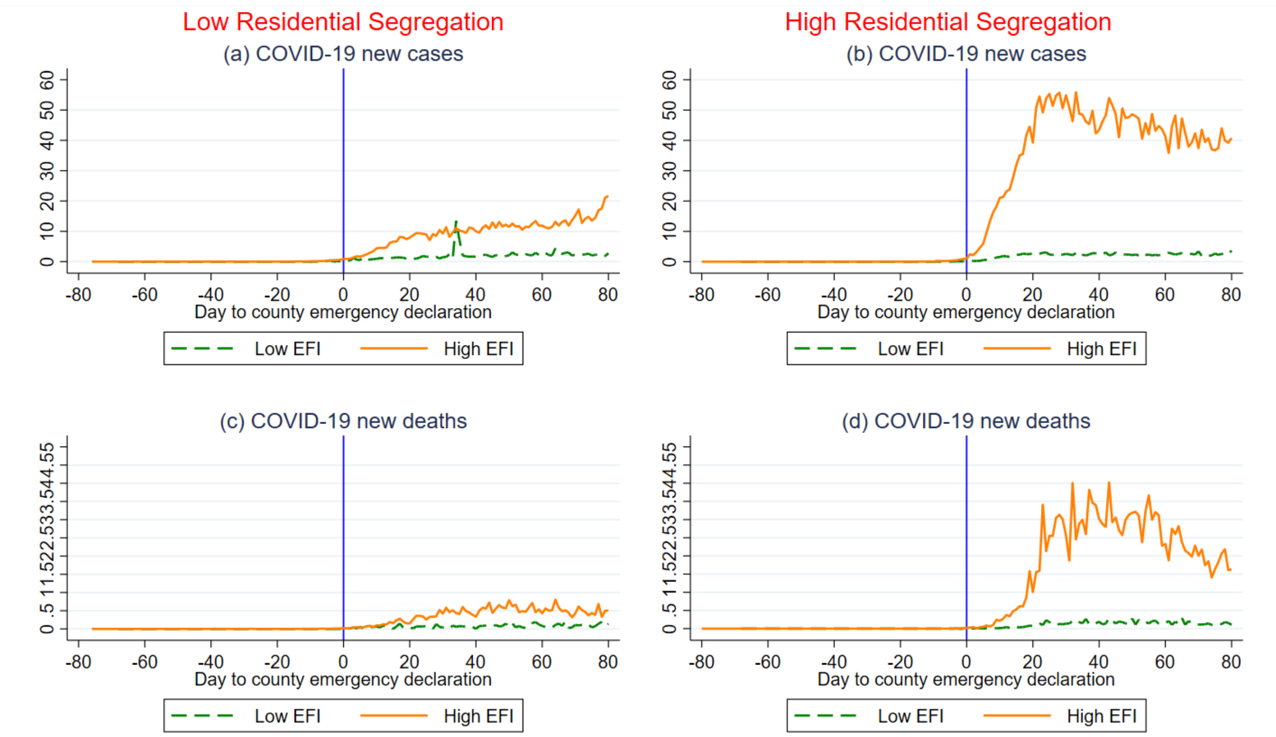
Note: Panel (a) of Figure 1 plots the average number of daily COVID-19 cases in counties in the U.S. relative to the date of their county-level State of Emergency declarations (denoted by the blue line at zero). The average number of new daily cases in the days preceding and following the county-level State of Emergency declarations is shown separately for counties with above-median values of ethnic fragmentation (shown in orange) and below-median values of ethnic fragmentation (shown in green), where ethnic fragmentation is defined for each county as the value of the Herfindahl-Hirschman Index. Panel (b) of Figure 2 plots the equivalent statistics for average daily deaths attributed to COVID-19 relative to the date of county-level State of Emergency declaration.

Figure 2: COVID-19 and county-level emergency declaration by level of racial segregation



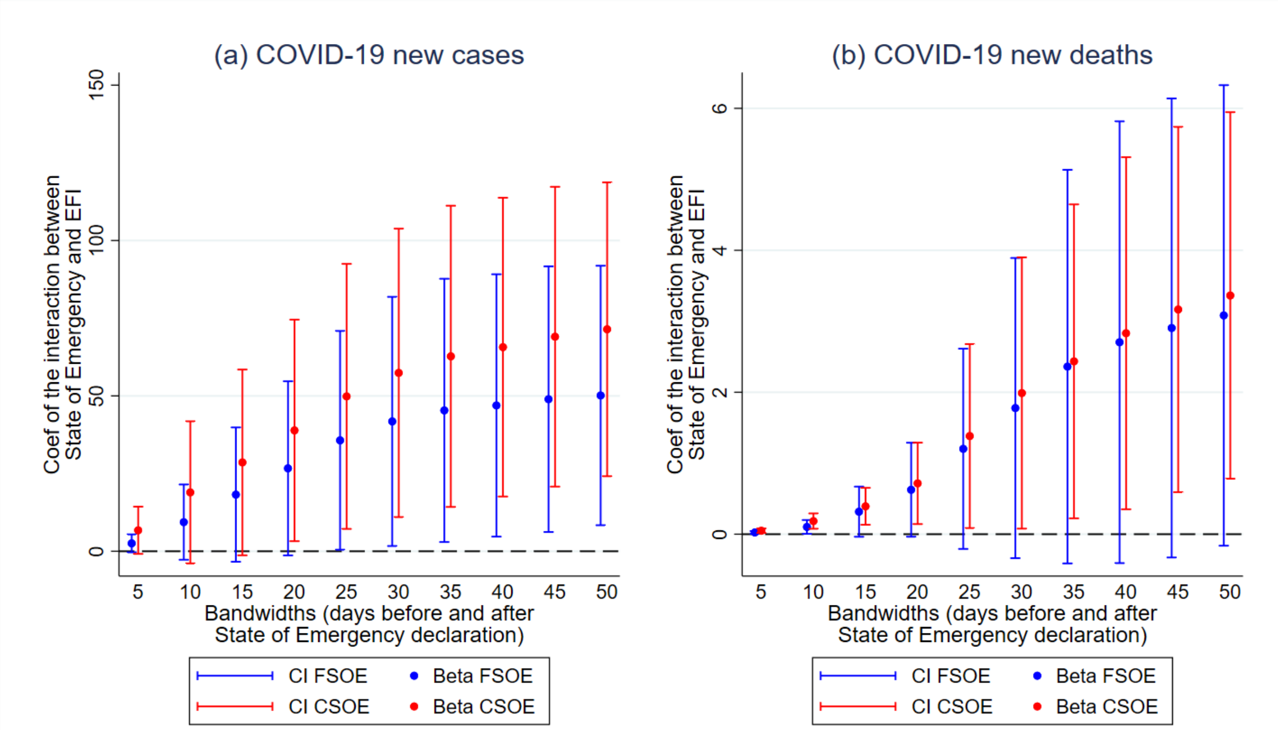
Note: Panel (a) of Figure 2 plots the average number of new daily COVID-19 cases in counties in the U.S. relative to the date of their county-level State of Emergency declarations (denoted by the blue line at zero). The average number of daily cases in the days preceding and following the county-level State of Emergency declarations is shown separately for counties with above-median values of White vs non-white racial residential segregation (shown in orange) and below-median values of Black-White racial residential segregation (shown in green), where the Black-White racial residential segregation is defined for each county in the 2018 American Community Survey. Panel (b) of Figure 3 plots the equivalent statistics for average daily deaths attributed to COVID-19 relative to the date of county-level State of Emergency declaration.

Figure 3: COVID-19 and county-level emergency declaration by level of ethnic fragmentation and racial segregation



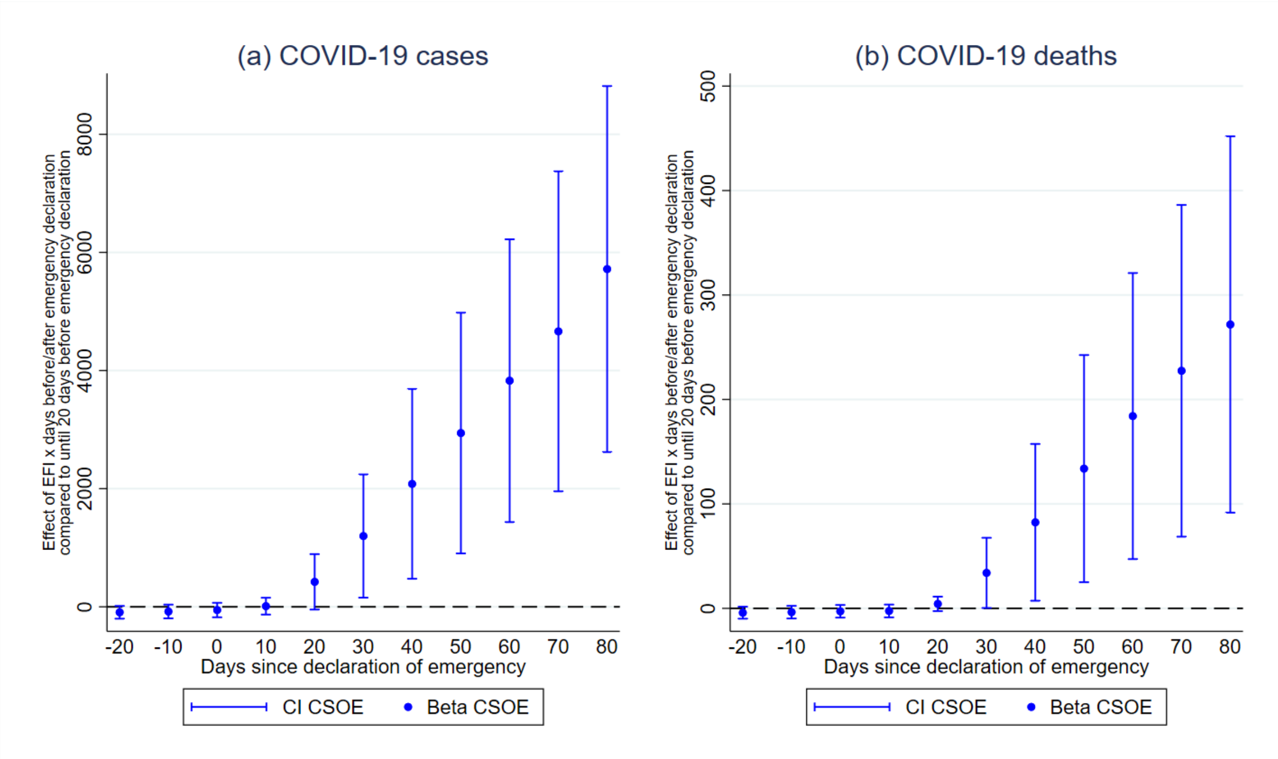
Note: Figure 3 plots the average number of new daily COVID-19 cases and deaths in U.S. counties relative to the date of their county-level State of Emergency declarations (denoted by the blue line), shown in separate graphs for counties with below-median (Panels a and c) and above-median (Panels b and d) levels of White vs non-white racial residential segregation. The average number of daily cases (Panels a and b) is shown for counties with above-median values of ethnic fragmentation (shown in orange) and below-median values of ethnic fragmentation (shown in green), where ethnic fragmentation is defined for each county as the value of the Herfindahl-Hirschman Index. Panels c and d of Figure 4 plot the equivalent statistics for average daily deaths attributed to COVID-19.

Figure 4: Dynamic of the effect of the interaction between emergency declarations and EFI on COVID-19 outcomes



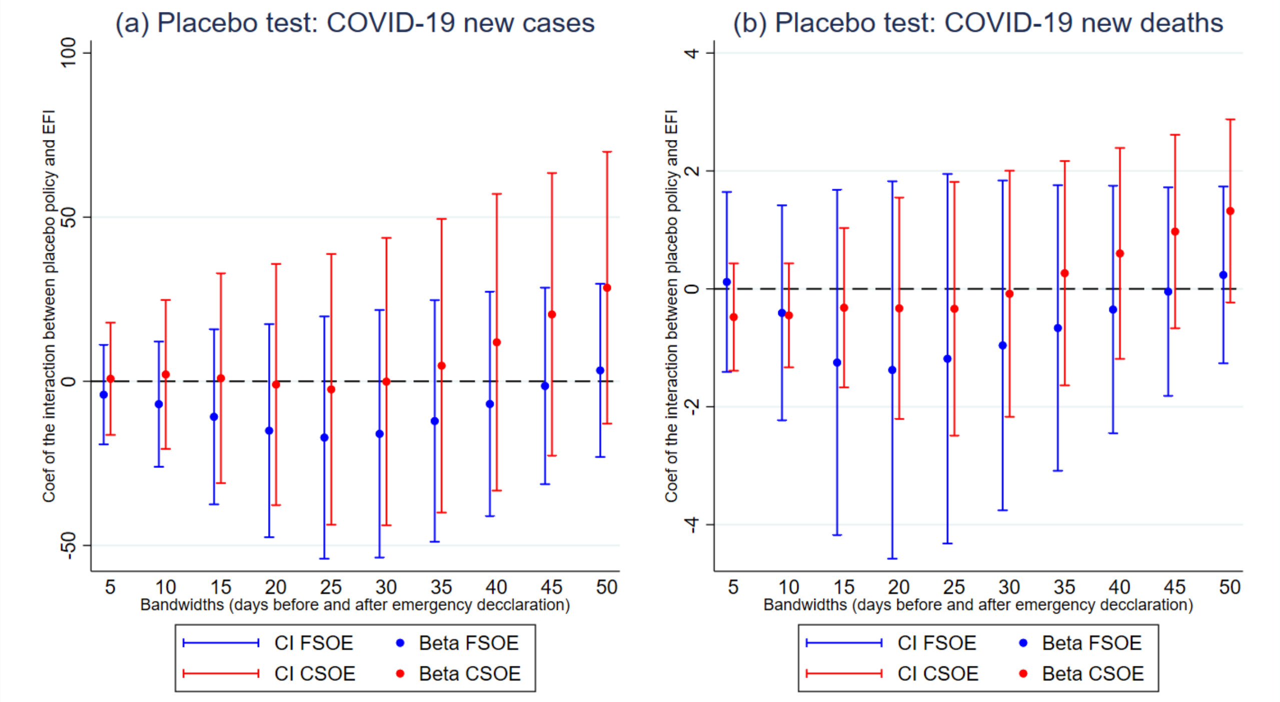
Note: Figure 4 summarizes, for different bin sizes around the policy dates, the regression coefficients and 95% confidence intervals of the interaction term between the Federal State of Emergency Declaration and EFI when equation 1 is estimated (denoted by FSOE, shown in blue), and the regression coefficient of the interaction term between the county-level State of Emergency Declaration and EFI when equation 2 is estimated (denoted by CSOE, shown in red). For example, 5 on the x-axis indicates a bin size of five days before and after the lockdown. Panel (a) shows coefficients of equations 1 and 2 when estimated for the outcome of new daily COVID-19 cases. Panel (b) shows coefficients of equations 1 and 2 when estimated for the outcome of new daily COVID-19 deaths. All specifications include county and day fixed effects. Standard errors are clustered at the state level.

Figure 5: Event-study estimates of the effect of the interaction between county-level emergency declaration and EFI on COVID-19 outcomes



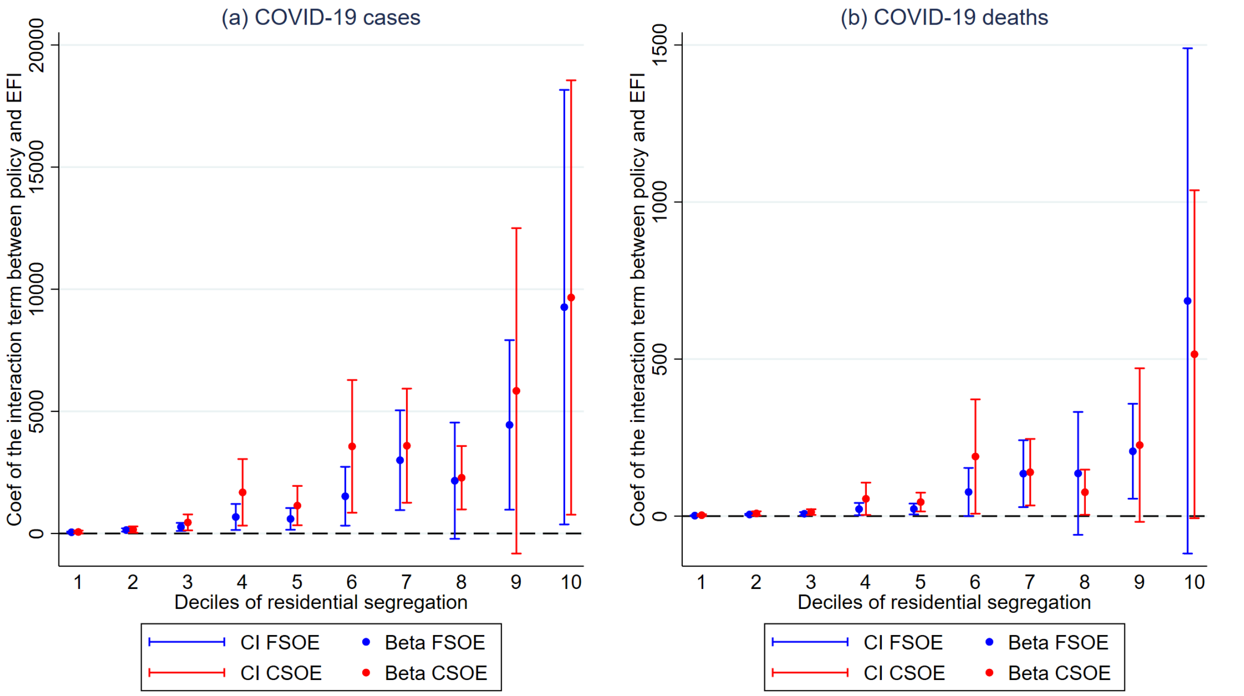
Note: Figure 5 summarizes, for different bin sizes, the event-study coefficients and 95% confidence intervals of the effect of interaction between the county-level State of Emergency declaration and EFI on COVID-19 outcomes when equation 3 is estimated. The vertical axis shows event-study estimates. The period from January 22, 2020 to until 31 days before the State of Emergency declaration is the reference period. The model includes dummies for each period of 10 days before and after the State of Emergency declaration. 95% confidence intervals around the estimated regression coefficients are plotted. All specifications include county and day fixed effects. Standard errors are clustered at the state level.

Figure 6: Placebo test: Dynamic of the effect of the interaction between fictitious emergency declarations and EFI on COVID-19 outcomes



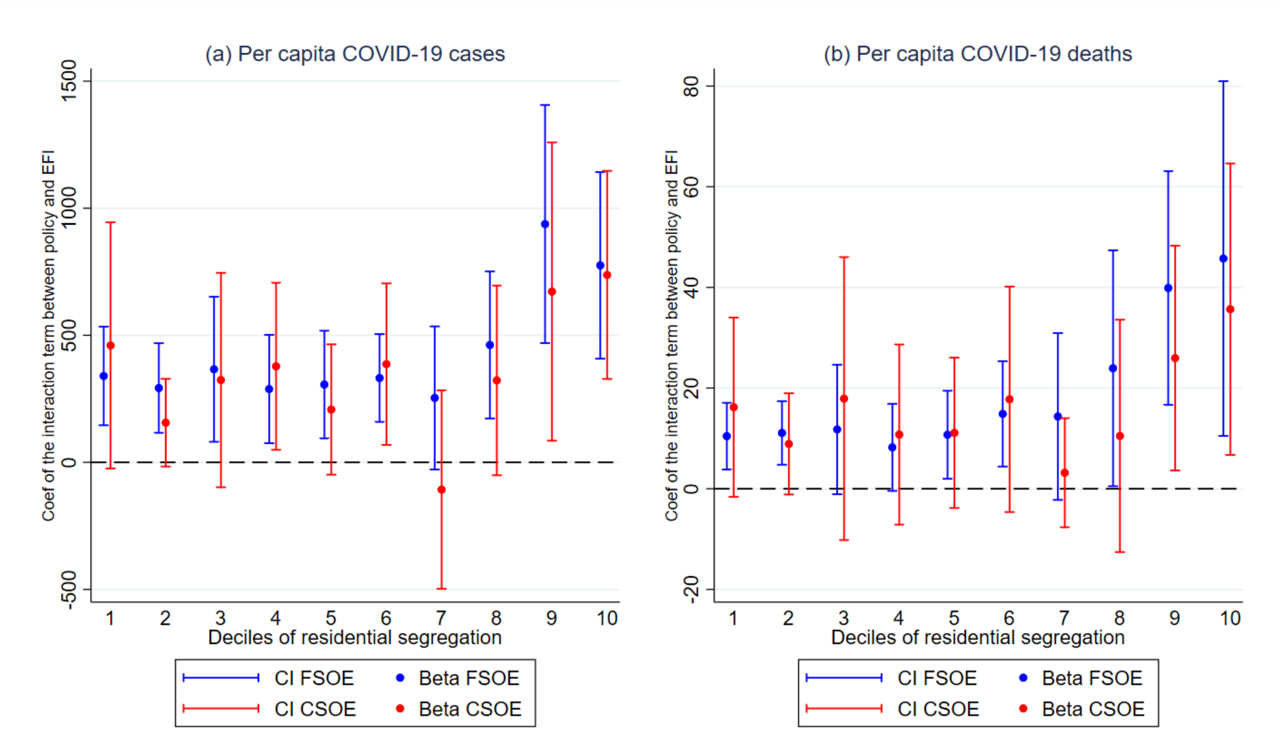
Note: Figure 6 summarizes, for different bin sizes around the fictitious policy dates, the regression coefficients and 95% confidence intervals of the interaction term between a placebo policy 45 days after the Federal State of Emergency Declaration and EFI when equation 1 is estimated (denoted by FSOE, shown in blue), and the regression coefficients of the interaction term between the a placebo policy 45 days after the county-level State of Emergency Declaration and EFI when equation 2 is estimated (denoted by CSOE, shown in red). For example, 5 on the x-axis indicates a bin size of five days before and after the placebo policy. Panel (a) shows coefficients of equations 1 and 2 when estimated for the outcome of new daily COVID-19 cases. Panel (b) shows coefficients of equations 1 and 2 when estimated for the outcome of new daily COVID-19 deaths. All specifications include county and day fixed effects. Standard errors are clustered at the state level.

Figure 7: Effect of the interaction between emergency declarations and EFI on COVID-19 outcomes by level of racial segregation



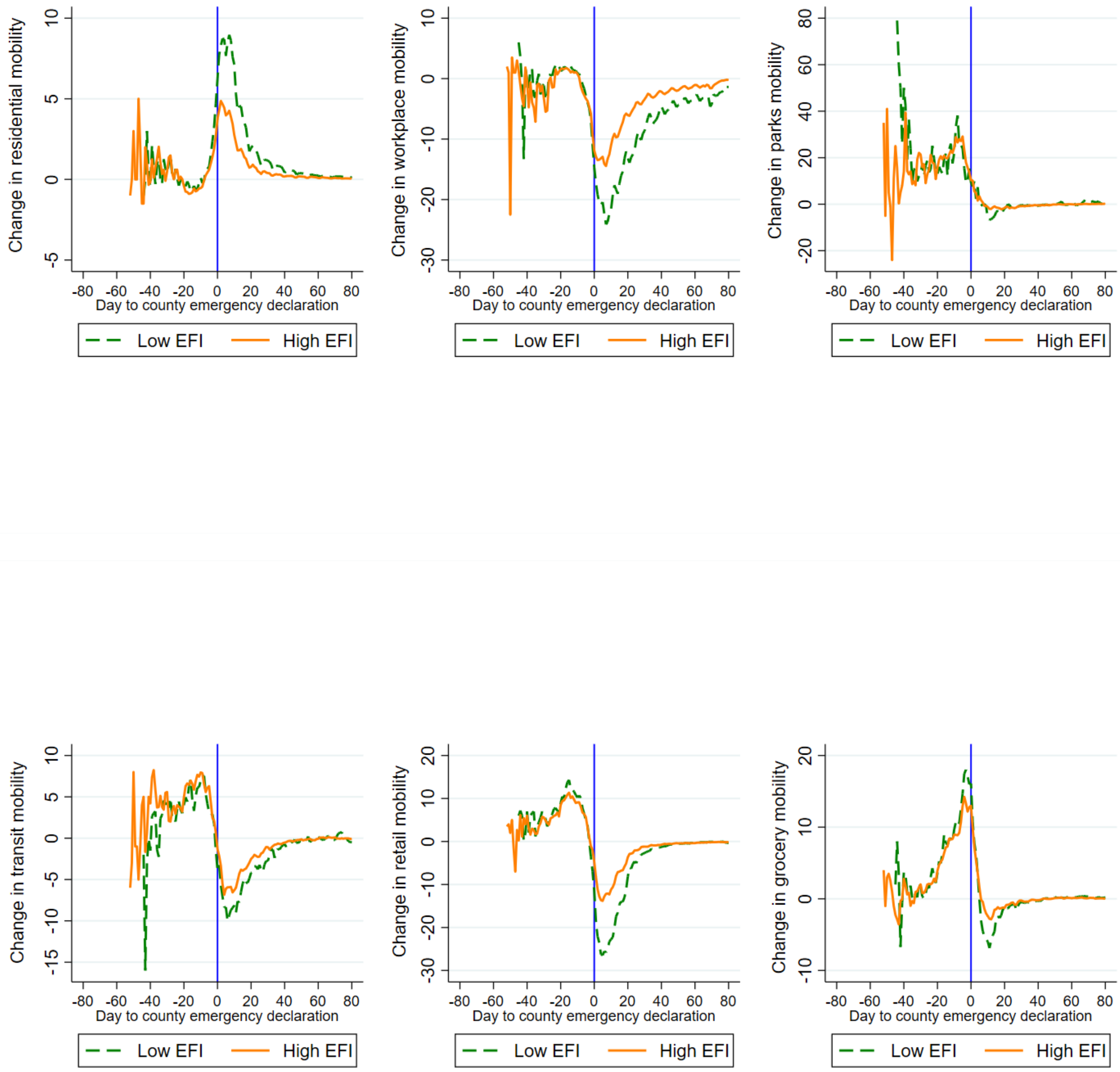
Note: Figure 7 summarizes the regression coefficients and 95% confidence intervals of the interaction term between the Federal State of Emergency Declaration and EFI when equation 1 is estimated (denoted by FSOE, shown in blue), and the regression coefficient of the interaction term between the county-level State of Emergency Declaration and EFI when equation 2 is estimated (denoted by CSOE, shown in red). Each regression is estimated separately for each decile of White vs non-white residential segregation. Panel (a) shows coefficients of equations 1 and 2 when estimated for the outcome of new daily COVID-19 cases. Panel (b) shows coefficients of equations 1 and 2 when estimated for the outcome of new daily COVID-19 deaths. All specifications include county and day fixed effects. Standard errors are clustered at the state level.

Figure 8: Effect of the interaction between emergency declarations and EFI on perc capita COVID-19 outcomes by level of racial segregation



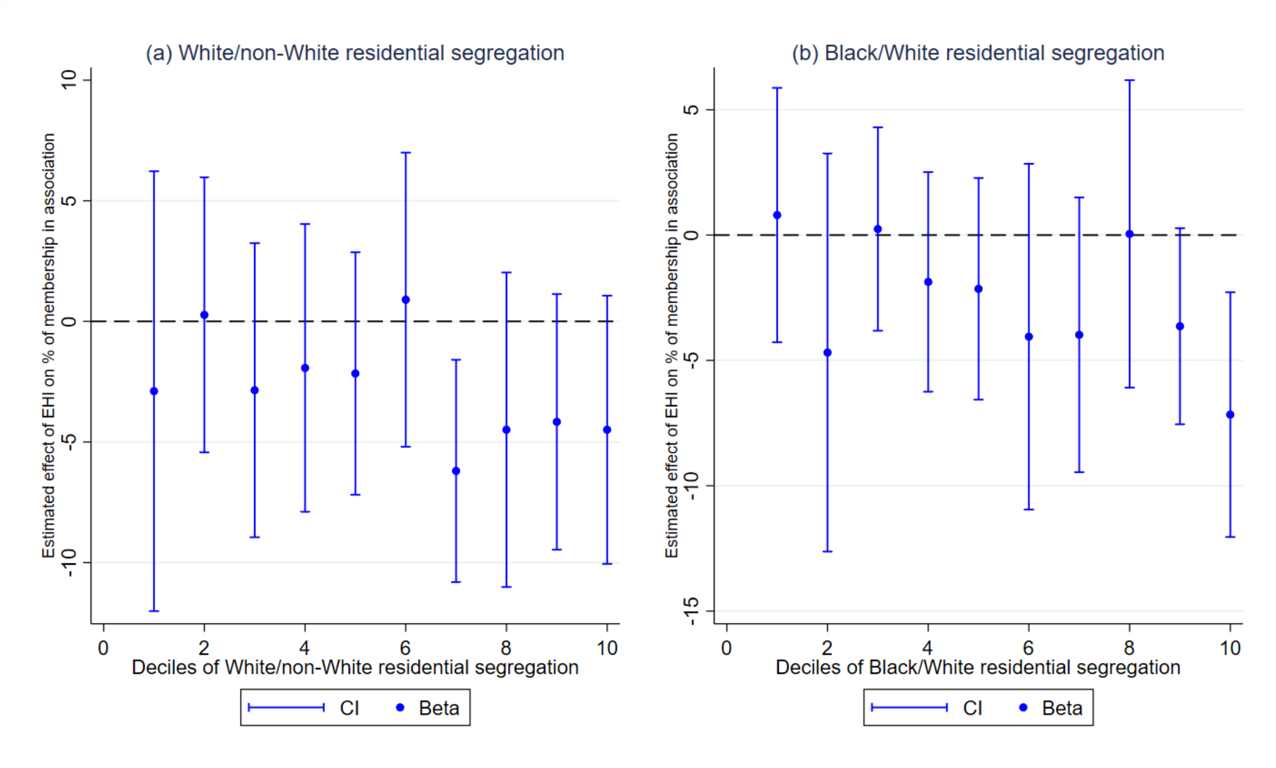
Note: Figure 8 summarizes the regression coefficients and 95% confidence intervals of the interaction term between the Federal State of Emergency Declaration and EFI when equation 1 is estimated (denoted by FSOE, shown in blue), and the regression coefficient of the interaction term between the county-level State of Emergency Declaration and EFI when equation 2 is estimated (denoted by CSOE, shown in red). Each regression is estimated separately for each decile of White vs non-white residential segregation. Panel (a) shows coefficients of equations 1 and 2 when estimated for the outcome of per capita COVID-19 cases. Panel (b) shows coefficients of equations 1 and 2 when estimated for the outcome of per capita COVID-19 deaths. All specifications include county and day fixed effects. Standard errors are clustered at the state level.

Figure 9: Mobility and county-level emergency declaration by level of ethnic fragmentation



Note: Figure 9 plots the average change in each of six measures of mobility relative to the date of implementation of county-level State of Emergency declarations using data from Google Community Mobility Reports. Changes in mobility are changes relative to the median value of frequency of visit and duration of stay for the same day of the week in a pre-pandemic reference week (January 3, 2020 through February 6, 2020). From left to right, top to bottom, mobility data are presented for change in visits to residences, workplaces, parks and outdoor spaces, transit stations, retailers and recreational outlets, and groceries and pharmacies. In each panel of the figure, changes in mobility are shown separately for counties with above-median values of ethnic fragmentation (shown in orange) and below-median values of ethnic fragmentation (shown in green), where ethnic fragmentation is defined for each county as the value of the Herfindahl-Hirschman Index. In this figure, mobility measures are adjusted for the cumulative number of COVID-19 cases.

Figure 10: Effect of EFI on social association rate by level of racial segregation



Note: Figure 10 reports of the coefficients of a regression of social association rate (measured as the number of membership associations per 10,000 individuals in a county) on EFI, estimated separately for each decile of White vs non-white residential segregation (figure 9a) and for each decile of Black vs White residential segregation (figure 9b). All specifications include state and day fixed effects. Data on social association rates are obtained from 2017 County Health Rankings.

Table 1: Descriptive Statistics of the Main Variables of Interest

	N	Mean	Std. de.	Min.	Max.
Total cases*	3,143	610.29	3307.51	0	82,427
Total death*	3,143	34.71	247.11	0	6,841
Duration of the pandemic	3,143	67.80	22.34	0	231
Ethnic Fragmentation Index	3,142	0.31	0.18	0	0.83
White vs non-white Residential segregation index	2,791	30.81	13.18	0	90
Black-White Residential segregation index	2,069	45.18	16.42	0	89
County with SOE (in %)	3,143	0.28	0.45	0	1
County with safer-at-home order (in %)	3,143	0.05	0.21	0	1
County with business closure (in %)	3,143	0.01	0.09	0	1
Residential**	1,541	1.15	1.20	-4	8.70
Workplace**	2,740	-6.70	6.91	-67	1.11
Retail**	2,528	-4.15	10.77	-66	47.64
Grocery**	2,438	2.95	6.63	-50	70.05
Transit**	1,133	-1.17	6.41	-51	33.87
Parks**	984	0.96	14.12	-63	193.00
Population density	3,117	431.96	2193.84	0	79761.45
Percentage of male	3,142	50.09	2.38	41	79.00
Median age	3,142	41.29	5.41	22	67.00
Poverty rate	3,141	15.60	6.48	2	55.10
Educational attainment	3,142	0.86	0.06	0	0.99
Urban population (in %)	3,140	0.41	0.32	0	1.00
Foreign-born (in %)	3,142	4.72	5.71	0	53.25
Adults with fair or poor health (in %)	3,142	17.94	4.74	8	40.99
Smokers (in %)	3,142	17.47	3.61	6	41.49
Adults with obesity (in %)	3,142	32.86	5.45	12	57.70
Adults with diabetes (in %)	3,142	12.12	4.06	2	34.10

Note: Table 1 presents descriptive statistics on county-level characteristics and COVID-19 outcomes. Mobility data are not available from Google Community Reports for all counties as Google does not release data for which insufficient observations of mobility exist. Sociodemographic variables are calculated from the 2018 American Community Survey. COVID-19 outcomes are compiled from USAFacts. County-level policy variables are retrieved from the National Association of Counties. *Average of the cumulative number of COVID-19 cases and deaths as of June 07, 2020. **Mobility measures are adjusted for the cumulative number of COVID-19 cases.

Table 2: Emergency declarations, ethnic fragmentation, and COVID-19 outcomes

	(1)	(2)	(3)	(4)	(5)
Government policy: National Emergency Declaration					
Panel A: Covid-19 cases					
Post Federal emergency declaration	284.95***	-345.70**			
	(82.98)	(149.28)			
EFI	1280.17**	0.34**	930.48*	-822.65**	
	(483.40)	(0.15)	(487.46)	(369.18)	
Post Federal emergency declaration × EFI		2030.08**	2030.08**	2103.26**	2030.08**
		(766.65)	(766.77)	(794.53)	(766.77)
Observations	433,596	433,596	433,596	426,696	433,596
Panel B: Covid-19 deaths					
Post Federal emergency declaration	15.77***	-21.15*			
	(5.74)	(11.66)	(.)		
EFI	74.93**	0.02	59.80	-55.05	
	(35.97)	(0.01)	(37.37)	(33.61)	
Post Federal emergency declaration × EFI		118.84**	118.84**	123.11**	118.84**
		(57.05)	(57.06)	(59.08)	(57.06)
Observations	433,596	433,596	433,596	426,696	433,596
Government policy: County Emergency Declaration					
Panel C: Covid-19 cases					
Post county emergency	532.70***	-617.52***	-1578.46***	-1774.11***	-1721.41***
	(137.89)	(204.98)	(484.65)	(508.96)	(471.89)
EFI	1931.77***	1.32***	1251.62**	-547.98	
	(561.13)	(0.43)	(506.34)	(439.15)	
Post county emergency × EFI		3224.40***	3221.71***	3065.13***	3038.86***
		(927.96)	(948.82)	(916.37)	(903.66)
Observations	119,370	119,370	119,370	118,128	119,370
Panel D: Covid-19 deaths					
Post county emergency	24.80***	-27.20**	-73.04***	-81.67***	-79.72***
	(7.03)	(10.77)	(25.37)	(25.71)	(24.22)
EFI	87.31***	0.03*	64.61**	-22.49	
	(29.46)	(0.02)	(27.52)	(16.68)	
Post county emergency × EFI		145.78***	145.82***	137.75***	137.41***
		(48.92)	(49.78)	(48.22)	(47.40)
Observations	119,370	119,370	119,370	118,128	119,370
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. population density, population size, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 3: Other mobility restriction policies, ethnic fragmentation, and COVID-19 outcomes

	(1)	(2)	(3)	(4)	(5)
Government policy: National Stringency Index					
Panel A: Covid-19 cases					
Stringency index	4.45***	-5.42**			
	(1.31)	(2.37)			
EFI	1215.94**	-265.48**	621.13	-1053.71**	
	(465.17)	(101.62)	(391.52)	(442.11)	
Stringency index × EFI		31.75**	31.75**	32.89**	31.75**
		(12.15)	(12.15)	(12.59)	(12.15)
Observations	424,170	424,170	424,170	417,420	424,170
Panel B: Covid-19 deaths					
Stringency index	0.25***	-0.33*			
	(0.09)	(0.18)			
EFI	71.04**	-15.54**	41.24	-68.52*	
	(34.40)	(7.54)	(29.45)	(39.56)	
Stringency index × EFI		1.86**	1.86**	1.92**	1.86**
		(0.90)	(0.90)	(0.93)	(0.90)
Observations	424,170	424,170	424,170	417,420	424,170
Government policy: County Safer-at-Home					
Panel C: Covid-19 cases					
Post county safer-at-home order	884.94***	-802.24**	-1945.57***	-2130.45***	-2090.13***
	(175.10)	(288.03)	(516.71)	(522.54)	(523.77)
EFI	1954.60***	8.50***	57.18	-2111.50**	
	(384.10)	(2.44)	(324.01)	(956.17)	
Post county safer-at-home order × EFI		3584.40***	3648.38***	3555.92***	3559.64***
		(669.13)	(744.42)	(671.46)	(689.96)
Observations	20,424	20,424	20,424	20,286	20,424
Panel D: Covid-19 deaths					
Post county safer-at-home order	31.66***	-27.77**	-73.47***	-80.34***	-78.25***
	(7.87)	(12.94)	(23.82)	(24.39)	(24.42)
EFI	68.73***	0.18***	3.18	-70.78	
	(19.66)	(0.06)	(15.10)	(46.01)	
Post county safer-at-home order × EFI		126.26***	128.35***	124.75***	124.64***
		(34.74)	(37.94)	(35.10)	(35.48)
Observations	20,424	20,424	20,424	20,286	20,424
Government policy: County Business Closure					
Panel E: Covid-19 cases					
Post county business closure	1737.71	-1816.66**	-4228.16**	-4392.75**	-4391.32**
	(951.12)	(633.00)	(1344.15)	(1496.28)	(1495.40)
EFI	4808.93***	14.25**	-3941.06	-4408.16**	
	(1406.67)	(5.75)	(2579.40)	(1466.85)	
Post county business closure × EFI		8735.92***	8878.28***	8751.58***	8747.93***
		(2513.79)	(2615.63)	(2609.13)	(2605.72)
Observations	3,726	3,726	3,726	3,726	3,726
Panel F: Covid-19 deaths					
Post county business closure	76.88*	-87.83**	-196.40**	-197.50**	-197.27**
	(41.38)	(35.16)	(66.82)	(69.33)	(69.30)
EFI	222.37**	0.19*	-146.74	-159.73*	
	(74.96)	(0.09)	(109.66)	(77.61)	
Post county business closure × EFI		404.82**	413.10**	408.00**	407.76**
		(134.34)	(138.92)	(138.81)	(138.62)
Observations	3,726	3,726	3,726	3,726	3,726
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. population density, population size, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 4: Emergency declarations, racial segregation, and COVID-19 outcomes

	(1)	(2)	(3)	(4)	(5)
Government policy: National Emergency Declaration					
Panel A: Covid-19 cases					
Post Federal emergency declaration	320.53***	-363.79**			
	(92.21)	(160.70)			
White/non-white Segr. index	14.00***	0.00**	-3.39	-12.58***	
	(4.97)	(0.00)	(2.06)	(4.53)	
Post Federal emergency declaration × White/non-white Segr. index		22.21***	22.21***	22.54***	22.21***
		(7.89)	(7.89)	(7.99)	(7.89)
Observations	385,158	385,158	385,158	380,328	385,158
Panel B: Covid-19 deaths					
Post Federal emergency declaration	17.74***	-25.67**			
	(6.40)	(12.22)			
White/non-white Segr. index	0.89**	0.00	-0.25*	-0.85**	
	(0.37)	(0.00)	(0.14)	(0.35)	
Post Federal emergency declaration × White/non-white Segr. index		1.41**	1.41**	1.43**	1.41**
		(0.59)	(0.59)	(0.59)	(0.59)
Observations	385,158	385,158	385,158	380,328	385,158
Government policy: County Emergency Declaration					
Panel C: Covid-19 cases					
Post county emergency	570.58***	-516.15*	-1327.73**	-1654.82***	-1612.33***
	(146.72)	(291.95)	(493.17)	(548.18)	(513.43)
White/non-white Segr. index	20.17**	0.01*	-3.81	-14.83**	
	(7.73)	(0.00)	(4.53)	(6.96)	
Post county emergency × White/non-white Segr. index		34.12**	33.77**	31.96**	31.79**
		(13.00)	(12.78)	(12.36)	(12.25)
Observations	112,056	112,056	112,056	111,090	112,056
Panel D: Covid-19 deaths					
Post county emergency	26.55***	-28.54*	-66.94**	-81.98***	-80.14***
	(7.46)	(15.94)	(26.59)	(28.72)	(27.42)
White/non-white Segr. index	1.02**	0.00	-0.25	-0.81**	
	(0.41)	(0.00)	(0.22)	(0.37)	
Post county emergency × White/non-white Segr. index		1.73**	1.71**	1.62**	1.61**
		(0.70)	(0.68)	(0.66)	(0.66)
Observations	112,056	112,056	112,056	111,090	112,056
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. population density, population size, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 5: Other mobility restriction policies, racial segregation, and COVID-19 outcomes

	(1)	(2)	(3)	(4)	(5)
Government policy: National Stringency Index					
Panel A: Covid-19 cases					
Stringency index	5.00***	-5.73**			
	(1.46)	(2.55)			
White/non-white Segr. index	13.34***	-2.92***	-6.19**	-14.94***	
	(4.79)	(1.05)	(2.94)	(5.40)	
Stringency index × White/non-white Segr. index		0.35***	0.35***	0.35***	0.35***
		(0.13)	(0.13)	(0.13)	(0.13)
Observations	376,785	376,785	376,785	372,060	376,785
Panel B: Covid-19 deaths					
Stringency index	0.28***	-0.40**			
	(0.10)	(0.19)			
White/non-white Segr. index	0.84**	-0.18**	-0.43**	-0.99**	
	(0.35)	(0.08)	(0.20)	(0.41)	
Stringency index × White/non-white Segr. index		0.02**	0.02**	0.02**	0.02**
		(0.01)	(0.01)	(0.01)	(0.01)
Observations	376,785	376,785	376,785	372,060	376,785
Government policy: County Safer-at-Home					
Panel C: Covid-19 cases					
Post county safer-at-home order	903.44***	-1612.70**	-2742.16***	-2878.71***	-2851.03***
	(185.20)	(598.39)	(745.58)	(718.50)	(723.47)
White/non-white Segr. index	43.74***	0.25**	3.06	-36.38**	
	(12.49)	(0.11)	(5.49)	(12.72)	
Post county safer-at-home order × White/non-white Segr. index		80.47***	80.51***	78.78***	79.24***
		(22.64)	(22.61)	(22.86)	(23.12)
Observations	20,286	20,286	20,286	20,148	20,286
Panel D: Covid-19 deaths					
Post county safer-at-home order	32.32***	-56.46**	-101.72***	-106.76***	-104.64***
	(8.31)	(21.63)	(28.32)	(27.57)	(28.09)
White/non-white Segr. index	1.54***	0.00*	0.16	-1.31**	
	(0.46)	(0.00)	(0.28)	(0.57)	
Post county safer-at-home order × White/non-white Segr. index		2.84***	2.84***	2.77***	2.77***
		(0.84)	(0.84)	(0.84)	(0.85)
Observations	20,286	20,286	20,286	20,148	20,286
Government policy: County Business Closure					
Panel E: Covid-19 cases					
Post county business closure	1886.69*	-1492.62	-3975.65*	-4085.89	-4076.55
	(955.18)	(1675.41)	(2161.08)	(2302.22)	(2300.31)
White/non-white Segr. index	52.00	0.11	-34.25	-55.25	
	(33.81)	(0.07)	(19.62)	(31.55)	
Post county business closure × White/non-white Segr. index		96.80	95.25	92.82	92.80
		(61.59)	(62.89)	(61.31)	(61.18)
Observations	3,450	3,450	3,450	3,450	3,450
Panel F: Covid-19 deaths					
Post county business closure	83.51*	-68.62	-181.93*	-178.75	-177.97
	(41.49)	(76.48)	(98.77)	(98.33)	(98.33)
White/non-white Segr. index	2.34	0.00	-1.64	-2.61	
	(1.54)	(0.00)	(1.04)	(1.44)	
Post county business closure × White/non-white Segr. index		4.36	4.29	4.20	4.20
		(2.81)	(2.86)	(2.81)	(2.81)
Observations	3,450	3,450	3,450	3,450	3,450
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. population density, population size, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 6: Emergency declarations, ethnic fragmentation, and COVID-19 by level of racial segregation

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
Government policy: National Emergency declaration				
Panel A: Covid-19 cases				
Post Federal emergency declaration	73.72***	574.70***		
	(10.07)	(177.44)		
EFI	208.63***	2646.75**		
	(50.81)	(991.55)		
Post Federal emergency declaration × EFI			330.85***	4197.18**
			(80.59)	(1573.13)
Observations	195,408	189,750	195,408	189,750
Panel B: Covid-19 deaths				
Post Federal emergency declaration	2.77***	33.16**		
	(0.39)	(12.43)		
EFI	7.07***	160.74**		
	(1.76)	(75.84)		
Post Federal emergency declaration × EFI			11.22***	254.91**
			(2.80)	(120.33)
Observations	195,408	189,750	195,408	189,750
Government policy: County Emergency declaration				
Panel C: Covid-19 cases				
Post county emergency	163.79***	936.31***	-388.36***	-3090.41***
	(24.66)	(261.40)	(93.14)	(880.56)
EFI	475.64***	3365.93***		
	(126.55)	(988.95)		
Post county emergency × EFI			778.09***	5335.91***
			(213.16)	(1615.59)
Observations	54,510	57,546	54,510	57,546
Panel D: Covid-19 deaths				
Post county emergency	6.20***	44.93***	-13.85***	-146.41***
	(0.89)	(13.28)	(3.08)	(44.88)
EFI	16.86***	155.99***		
	(4.20)	(52.66)		
Post county emergency × EFI			27.67***	247.88***
			(7.06)	(85.99)
Observations	54,510	57,546	54,510	57,546
County FE			✓	✓
Day FE			✓	✓

Note: Each column of each panel reports coefficients from a separate regression. "High res. seg." and "Low res. seg." refer to regressions limited to counties with above- and below-median values of racial residential segregation, respectively. The dependent variable in each regression is denoted by the corresponding panel title. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 7: Other mobility restriction policies, ethnic fragmentation, and COVID-19 by level of racial segregation

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
Government policy: National Stringency index				
Panel A: Covid-19 cases				
Stringency index	1.13***	8.98***		
	(0.15)	(2.81)		
EFI	193.63***	2518.99**		
	(47.06)	(955.71)		
Stringency index × EFI			5.06***	65.77**
			(1.23)	(24.96)
Observations	191,160	185,625	191,160	185,625
Panel B: Covid-19 deaths				
Stringency index	0.04***	0.52**		
	(0.01)	(0.20)		
EFI	6.62***	152.51**		
	(1.65)	(72.61)		
Stringency index × EFI			0.17***	3.98**
			(0.04)	(1.90)
Observations	191,160	185,625	191,160	185,625
Government policy: County Safer-at-Home				
Panel C: Covid-19 cases				
Post county safer-at-home order	282.71***	1489.51***	-189.94	-3337.49***
	(54.40)	(372.79)	(121.87)	(919.80)
EFI	201.07	2765.83***		
	(120.21)	(526.83)		
Post county safer-at-home order × EFI			399.66	5128.87***
			(224.58)	(1034.22)
Observations	10,074	10,212	10,074	10,212
Panel D: Covid-19 deaths				
Post county safer-at-home order	10.32***	53.09***	-2.90	-129.77**
	(2.96)	(16.65)	(5.31)	(44.12)
EFI	2.94	99.83***		
	(4.64)	(29.08)		
Post county safer-at-home order × EFI			6.41	184.63***
			(9.09)	(55.91)
Observations	10,074	10,212	10,074	10,212
Government policy: County Business closure				
Panel E: Covid-19 cases				
Post county business closure	111.75	3042.94**	-113.10	-7461.37***
	(83.49)	(1143.31)	(67.69)	(1984.46)
EFI	231.99**	6415.42**		
	(69.06)	(1980.32)		
Post county business closure × EFI			416.08*	12165.55**
			(144.91)	(3757.46)
Observations	1,380	2,070	1,380	2,070
Panel F: Covid-19 deaths				
Post county business closure	5.73	134.01**	-8.55	-347.51**
	(4.77)	(51.51)	(4.23)	(118.25)
EFI	14.56***	311.03**		
	(2.41)	(110.99)		
Post county business closure × EFI			26.17**	592.77**
			(5.65)	(212.71)
Observations	1,380	2,070	1,380	2,070
County FE			✓	✓
Day FE			✓	✓

Note: Each column of each panel reports coefficients from a separate regression. "High res. seg." and "Low res. seg." refer to regressions limited to counties with above- and below-median values of racial residential segregation, respectively. The dependent variable in each regression is denoted by the corresponding panel title. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 8: Federal state of emergency, ethnic fragmentation, and Google mobility measures

	(1)	(2)	(3)	(4)	(5)
Panel A: Retail					
Post Federal emergency declaration	-15.80***	-22.03***			
	(0.57)	(0.90)			
EFI	9.53***	-3.15**	-3.74***	-7.53***	
	(1.50)	(1.40)	(1.34)	(2.15)	
Post Federal emergency declaration × EFI		18.85***	16.17***	16.33***	17.72***
		(2.45)	(1.99)	(2.06)	(2.10)
Observations	194,738	194,738	194,738	194,425	194,722
Panel B: Grocery					
Post Federal emergency declaration	-3.65***	-4.04***			
	(0.31)	(0.37)			
EFI	-1.83*	-2.57**	-2.36*	0.58	
	(1.02)	(1.24)	(1.22)	(1.12)	
Post Federal emergency declaration × EFI		1.13	1.90	1.96	1.95
		(1.31)	(1.34)	(1.37)	(1.52)
Observations	184,737	184,737	184,737	184,459	184,718
Panel C: Parks					
Post Federal emergency declaration	-19.63***	-20.26***			
	(1.37)	(2.05)			
EFI	-1.26	-2.35	4.01	0.22	
	(2.07)	(4.74)	(4.35)	(3.90)	
Post Federal emergency declaration × EFI		1.49	1.73	1.64	0.40
		(4.06)	(4.00)	(4.04)	(4.11)
Observations	65,129	65,129	65,129	65,129	65,066
Panel D: Transit					
Post Federal emergency declaration	-7.82***	-9.35***			
	(0.58)	(0.74)			
EFI	1.64	-1.30	-0.20	-1.28	
	(1.17)	(2.17)	(2.81)	(2.23)	
Post Federal emergency declaration × EFI		3.91**	4.05**	4.06**	4.07**
		(1.80)	(1.79)	(1.78)	(1.75)
Observations	102,118	102,118	102,118	102,118	102,102
Panel E: Workplace					
Post Federal emergency declaration	-8.54***	-13.95***			
	(0.58)	(0.81)			
EFI	9.56***	-3.09***	-1.27	-9.08***	
	(1.31)	(0.69)	(1.57)	(1.93)	
Post Federal emergency declaration × EFI		16.88***	16.70***	16.68***	16.29***
		(1.98)	(1.96)	(1.95)	(1.94)
Observations	261,011	261,011	261,011	260,566	261,000
Panel F: Residential					
Post Federal emergency declaration	1.87***	3.06***			
	(0.13)	(0.19)			
EFI	-2.75***	-0.40*	-0.49	0.97***	
	(0.30)	(0.21)	(0.33)	(0.31)	
Post Federal emergency declaration × EFI		-3.32***	-3.36***	-3.40***	-3.38***
		(0.48)	(0.51)	(0.50)	(0.50)
Observations	120,706	120,706	120,706	120,594	120,699
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: In this table, mobility measures are adjusted for the cumulative number of COVID-19 cases. Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. population density, population size, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 9: County state of emergency, ethnic fragmentation, and Google mobility measures

	(1)	(2)	(3)	(4)	(5)
Panel A: Retail					
Post county emergency	-11.57***	-18.11***	-8.52***	-8.97***	-10.24***
	(0.70)	(1.36)	(1.31)	(1.36)	(1.34)
EFI	8.50***	-2.73*	-2.25	-6.66**	
	(1.10)	(1.57)	(1.78)	(2.67)	
Post county emergency × EFI		17.42***	15.59***	15.92***	17.52***
		(2.81)	(2.27)	(2.36)	(2.40)
Observations	67,239	67,239	67,239	66,928	67,235
Panel B: Grocery					
Post county emergency	-7.09***	-8.87***	-6.49***	-6.40***	-6.81***
	(0.38)	(0.50)	(0.94)	(0.89)	(0.85)
EFI	-0.07	-3.05*	-3.26**	-0.40	
	(0.93)	(1.81)	(1.45)	(1.40)	
Post county emergency × EFI		4.68***	3.28**	3.52**	4.03**
		(1.70)	(1.57)	(1.58)	(1.76)
Observations	65,056	65,056	65,056	64,779	65,053
Panel C: Parks					
Post county emergency	-19.60***	-23.09***	-11.08***	-10.99***	-11.18***
	(1.59)	(3.36)	(3.87)	(3.84)	(3.93)
EFI	-1.34	-6.83	-0.66	-4.27	
	(3.05)	(6.47)	(6.20)	(5.40)	
Post county emergency × EFI		7.76	6.96	7.27	7.32
		(5.43)	(5.62)	(5.64)	(5.64)
Observations	34,310	34,310	34,310	34,310	34,295
Panel D: Transit					
Post county emergency	-6.55***	-8.49***	-8.19***	-8.14***	-8.30***
	(0.49)	(1.75)	(2.10)	(2.04)	(1.95)
EFI	2.34	-0.91	-1.24	-3.91	
	(1.74)	(3.99)	(4.20)	(3.85)	
Post county emergency × EFI		4.53	4.90	4.81	5.01
		(3.38)	(3.49)	(3.45)	(3.39)
Observations	42,907	42,907	42,907	42,907	42,899
Panel E: Workplace					
Post county emergency	-5.08***	-11.17***	-6.05***	-6.62***	-6.63***
	(0.77)	(1.27)	(1.01)	(1.00)	(1.06)
EFI	9.87***	-1.94**	-0.87	-10.96***	
	(1.54)	(0.96)	(1.84)	(2.37)	
Post county emergency × EFI		16.66***	16.76***	16.53***	16.04***
		(2.46)	(2.18)	(2.13)	(2.07)
Observations	80,004	80,004	80,004	79,634	80,002
Panel F: Residential					
Post county emergency	0.89***	1.92***	0.85**	0.98***	1.01***
	(0.13)	(0.28)	(0.32)	(0.32)	(0.33)
EFI	-2.65***	-0.89***	-1.14***	0.60	
	(0.31)	(0.28)	(0.28)	(0.36)	
Post county emergency × EFI		-2.56***	-2.94***	-2.95***	-2.92***
		(0.57)	(0.36)	(0.38)	(0.38)
Observations	49,424	49,424	49,424	49,312	49,423
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: In this table, mobility measures are adjusted for the cumulative number of COVID-19 cases. Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. population density, population size, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 10: Federal state of emergency, ethnic fragmentation, and Google mobility measures by level of racial segregation

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
Panel A: Retail				
Post Federal emergency declaration	-17.21***	-14.56***		
	(0.60)	(0.64)		
EFI	8.92***	9.60***		
	(1.63)	(1.40)		
Post Federal emergency declaration × EFI			15.70***	19.21***
			(2.51)	(2.05)
Observations	86,968	106,931	86,956	106,929
Panel B: Grocery				
Post Federal emergency declaration	-3.50***	-3.78***		
	(0.48)	(0.26)		
EFI	-2.57*	-1.27		
	(1.32)	(1.06)		
Post Federal emergency declaration × EFI			1.81	1.91*
			(2.34)	(1.13)
Observations	82,422	101,306	82,410	101,302
Panel C: Parks				
Post Federal emergency declaration	-19.35***	-19.79***		
	(2.12)	(1.40)		
EFI	-5.14	-0.60		
	(4.22)	(1.80)		
Post Federal emergency declaration × EFI			0.90	1.13
			(6.36)	(4.61)
Observations	23,686	41,252	23,657	41,218
Panel D: Transit				
Post Federal emergency declaration	-9.05***	-6.86***		
	(0.90)	(0.35)		
EFI	2.87	1.28		
	(2.48)	(0.87)		
Post Federal emergency declaration × EFI			-1.08	7.47***
			(2.31)	(2.23)
Observations	39,987	60,776	39,983	60,765
Panel E: Workplace				
Post Federal emergency declaration	-9.57***	-7.15***		
	(0.61)	(0.62)		
EFI	8.00***	9.99***		
	(1.23)	(1.34)		
Post Federal emergency declaration × EFI			14.66***	17.17***
			(2.18)	(1.87)
Observations	125,645	131,133	125,640	131,131
Panel F: Residential				
Post Federal emergency declaration	2.21***	1.67***		
	(0.15)	(0.14)		
EFI	-2.22***	-3.10***		
	(0.40)	(0.31)		
Post Federal emergency declaration × EFI			-2.62***	-3.90***
			(0.74)	(0.45)
Observations	45,742	74,964	45,737	74,962
County FE			✓	✓
Day FE			✓	✓
Controls				

Note: In this table, mobility measures are adjusted for the cumulative number of COVID-19 cases. Each column of each panel reports coefficients from a separate regression. "High res. seg." and "Low res. seg." refer to regressions limited to counties with above- and below-median values of racial residential segregation, respectively. The dependent variable in each regression is denoted by the corresponding panel title. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 11: County state of emergency, ethnic fragmentation, and Google mobility measures by level of racial segregation

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
	Panel A: Retail			
Post county emergency	-12.35***	-10.93***	-9.45***	-10.96***
	(0.72)	(0.86)	(1.65)	(1.58)
EFI	7.62***	8.67***		
	(1.77)	(0.97)		
Post county emergency × EFI			14.58***	19.90***
			(2.79)	(3.04)
Observations	30,358	36,742	30,355	36,741
	Panel B: Grocery			
Post county emergency	-7.31***	-6.89***	-5.58***	-7.89***
	(0.48)	(0.46)	(1.17)	(0.94)
EFI	-0.19	-0.07		
	(1.06)	(1.23)		
Post county emergency × EFI			2.71	4.91**
			(2.45)	(1.90)
Observations	29,536	35,327	29,535	35,325
	Panel C: Parks			
Post county emergency	-19.83***	-19.46***	-12.51**	-11.15**
	(2.46)	(1.75)	(5.29)	(4.21)
EFI	-0.28	-3.23		
	(6.45)	(2.37)		
Post county emergency × EFI			10.81	6.67
			(9.02)	(6.82)
Observations	14,083	20,195	14,077	20,186
	Panel D: Transit			
Post county emergency	-7.24***	-6.00***	-7.32*	-8.25***
	(0.85)	(0.40)	(3.89)	(1.66)
EFI	3.97	1.44		
	(4.55)	(1.22)		
Post county emergency × EFI			-2.30	9.38***
			(7.23)	(3.19)
Observations	17,483	25,169	17,480	25,164
	Panel E: Workplace			
Post county emergency	-5.32***	-4.56***	-6.32***	-6.63***
	(0.84)	(0.79)	(1.31)	(1.05)
EFI	8.04***	10.48***		
	(2.04)	(1.47)		
Post county emergency × EFI			14.46***	16.54***
			(2.56)	(2.01)
Observations	37,725	41,603	37,724	41,602
	Panel F: Residential			
Post county emergency	1.05***	0.78***	0.71*	1.21***
	(0.18)	(0.13)	(0.41)	(0.38)
EFI	-2.01***	-3.07***		
	(0.39)	(0.40)		
Post county emergency × EFI			-2.03***	-3.50***
			(0.49)	(0.51)
Observations	20,381	29,043	20,380	29,043
County FE			✓	✓
Day FE			✓	✓

Note: Each column of each panel reports coefficients from a separate regression. "High res. seg." and "Low res. seg." refer to regressions limited to counties with above- and below-median values of racial residential segregation, respectively. The dependent variable in each regression is denoted by the corresponding panel title. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table 12: Mask wearing, ethnic fragmentation, and racial segregation

	(1)	(2)	(3)	(4)	(5)
Panel A: Share of people who say that they frequently wear a mask					
EFI	-0.070***		-0.021***		-0.037***
	(0.013)		(0.003)		(0.008)
Black/White Segr. index		-0.009**	-0.012***		
		(0.004)	(0.004)		
White/non-white Segr. index				-0.037***	-0.029***
				(0.009)	(0.008)
Observations	2,983	2,063	2,063	2,745	2,745
Panel B: Share of people who say that they always wear a mask					
EFI	-0.151***		-0.045***		-0.082***
	(0.022)		(0.007)		(0.015)
Black/White Segr. index		-0.024**	-0.031***		
		(0.010)	(0.010)		
White/non-white Segr. index				-0.088***	-0.070***
				(0.021)	(0.020)
Observations	2,983	2,063	2,063	2,745	2,745
State FE	✓	✓	✓	✓	✓

Note: In all specifications, the measure of mask wearing is adjusted for the cumulative number of COVID-19 cases reported in June 7, 2020 (the date on which the self-reported mask wearing data was collected). Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

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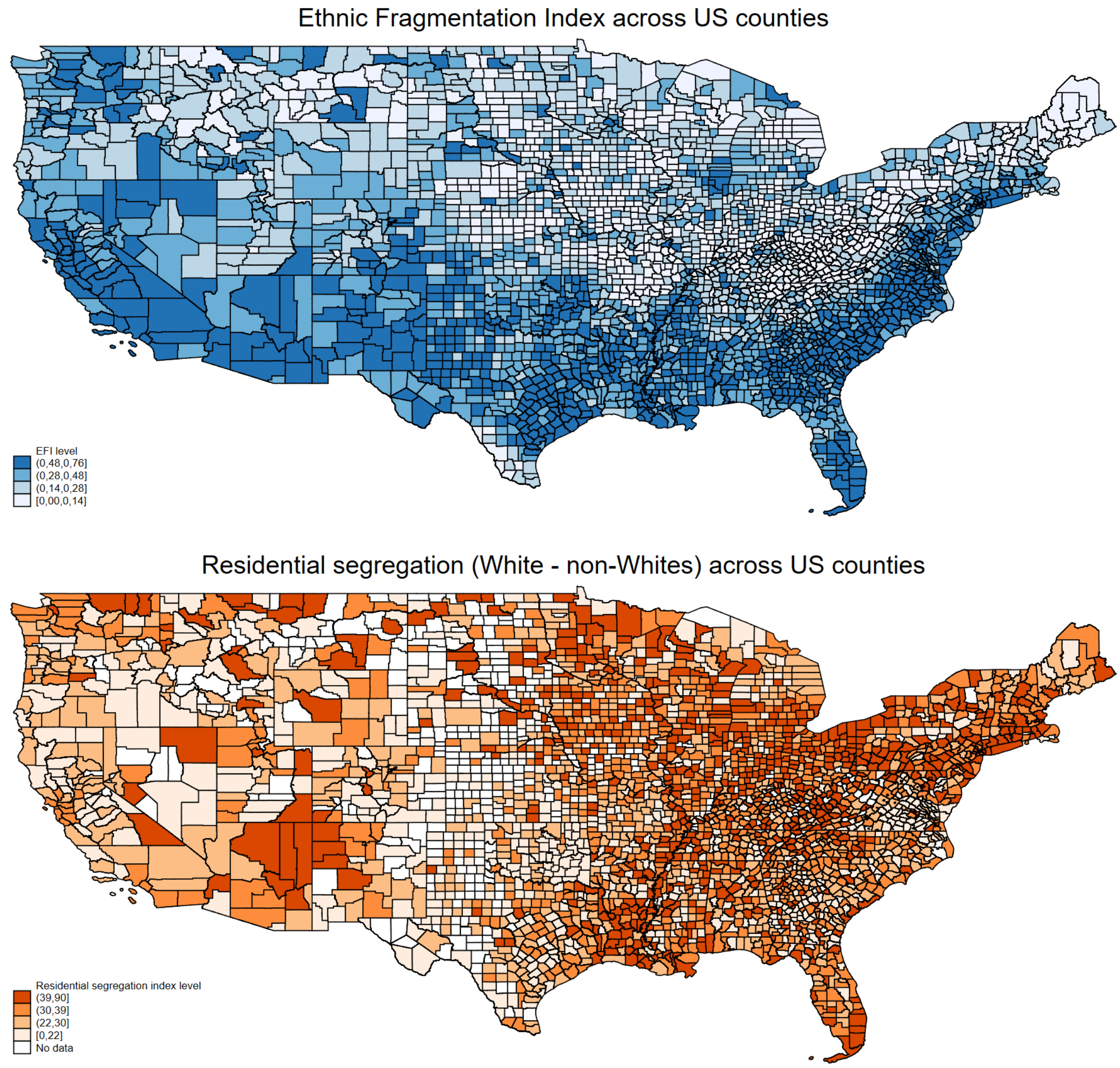
Appendix A

Figure A1



Note: The top graphic depicts county-level ethnic fragmentation across the continental United States. As colors progress from white to blue, the level of ethnic fragmentation increases. The bottom graphic shows county-level residential segregation between White and Non-White residents in the United States as measured by a dissimilarity index. As colors progress from pale orange to red, the level of racial residential segregation in the county increases. Both graphs are generated by the authors using data from the 2018 American Community Survey.

Table A1: Emergency declarations, racial segregation (Black vs White), and COVID-19 outcomes

	(1)	(2)	(3)	(4)	(5)
Government policy: National Emergency Declaration					
Panel A: Covid-19 cases					
Post Federal emergency declaration	428.31***	-444.00			
	(123.98)	(269.17)			
Black/White Segr. index	12.17**	0.00**	-2.87*	-10.07**	
	(5.24)	(0.00)	(1.68)	(4.55)	
Post Federal emergency declaration × Black/White Segr. index		19.31**	19.31**	19.42**	19.31**
		(8.31)	(8.31)	(8.37)	(8.31)
Observations	285,522	285,522	285,522	282,624	285,522
Panel B: Covid-19 deaths					
Post Federal emergency declaration	23.76***	-34.08			
	(8.61)	(21.21)			
Black/White Segr. index	0.81**	0.00	-0.21**	-0.74**	
	(0.40)	(0.00)	(0.10)	(0.33)	
Post Federal emergency declaration × Black/White Segr. index		1.28**	1.28**	1.29*	1.28**
		(0.64)	(0.64)	(0.64)	(0.64)
Observations	285,522	285,522	285,522	282,624	285,522
Government policy: County Emergency Declaration					
Panel C: Covid-19 cases					
Post county emergency	684.82***	-799.55	-1751.72**	-2147.21**	-2061.25**
	(172.93)	(516.33)	(748.16)	(821.45)	(768.43)
Black/White Segr. index	18.82**	0.00	-2.18	-11.42	
	(8.38)	(0.00)	(4.22)	(6.92)	
Post county emergency × Black/White Segr. index		31.74**	31.52**	30.79**	29.72**
		(14.08)	(13.91)	(13.76)	(13.36)
Observations	92,184	92,184	92,184	91,494	92,184
Panel D: Covid-19 deaths					
Post county emergency	31.87***	-44.67	-89.73**	-107.92**	-104.00**
	(8.88)	(27.07)	(39.51)	(42.52)	(40.37)
Black/White Segr. index	0.97**	-0.00	-0.23	-0.77**	
	(0.44)	(0.00)	(0.20)	(0.37)	
Post county emergency × Black/White Segr. index		1.64**	1.62**	1.58**	1.53**
		(0.73)	(0.72)	(0.72)	(0.70)
Observations	92,184	92,184	92,184	91,494	92,184
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column is from a separate regression. Ethnic divisions is measured by the level of residential segregation between Whites and non-Whites. *Controls* include county-level characteristics (i.e. population density, percentage of males, average age, poverty, education, urban area, the percentage of immigrants) and county-level health characteristics (i.e. the percentage of adults with obesity, "poor health", diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table A2: Other mobility restriction policies, racial segregation (Black vs White), and COVID-19 outcomes

	(1)	(2)	(3)	(4)	(5)
Government policy: National Stringency Index					
Panel A: Covid-19 cases					
Stringency index	6.68***	-7.04			
	(1.96)	(4.27)			
Black/White Segr. index	11.63**	-2.54**	-5.30**	-12.19**	
	(5.05)	(1.10)	(2.56)	(5.44)	
Stringency index × Black/White Segr. index		0.30**	0.30**	0.31**	0.30**
		(0.13)	(0.13)	(0.13)	(0.13)
Observations	279,315	279,315	279,315	276,480	279,315
Panel B: Covid-19 deaths					
Stringency index	0.37***	-0.53			
	(0.14)	(0.33)			
Black/White Segr. index	0.77*	-0.17*	-0.37**	-0.87**	
	(0.38)	(0.08)	(0.17)	(0.40)	
Stringency index × Black/White Segr. index		0.02*	0.02*	0.02*	0.02*
		(0.01)	(0.01)	(0.01)	(0.01)
Observations	279,315	279,315	279,315	276,480	279,315
Government policy: County Safer-at-Home					
Panel C: Covid-19 cases					
Post county safer-at-home order	968.12***	-1327.60*	-2504.13**	-2714.85***	-2661.59***
	(186.76)	(627.89)	(844.14)	(813.51)	(808.44)
Black/White Segr. index	27.75***	0.12	-0.66	-22.90***	
	(9.28)	(0.07)	(2.48)	(7.07)	
Post county safer-at-home order × Black/White Segr. index		51.13***	51.44***	50.77**	50.51**
		(16.80)	(17.13)	(17.21)	(17.20)
Observations	18,630	18,630	18,630	18,492	18,630
Panel D: Covid-19 deaths					
Post county safer-at-home order	34.74***	-52.20**	-99.63***	-107.49***	-104.23***
	(8.67)	(22.42)	(32.55)	(32.37)	(32.21)
Black/White Segr. index	1.05***	-0.00	-0.10	-0.96**	
	(0.34)	(0.00)	(0.12)	(0.32)	
Post county safer-at-home order × Black/White Segr. index		1.94***	1.95***	1.91***	1.89***
		(0.62)	(0.64)	(0.63)	(0.63)
Observations	18,630	18,630	18,630	18,492	18,630
Government policy: County Business Closure					
Panel E: Covid-19 cases					
Post county business closure	2449.57*	-2666.46	-5974.72	-5984.31	-5984.31
	(1096.51)	(2370.83)	(3379.89)	(3441.74)	(3434.79)
Black/White Segr. index	54.76	0.08	-18.58	-22.63	
	(33.04)	(0.07)	(59.86)	(33.75)	
Post county business closure × Black/White Segr. index		99.83	98.63	98.32	98.32
		(59.71)	(62.66)	(61.75)	(61.62)
Observations	2,622	2,622	2,622	2,622	2,622
Panel F: Covid-19 deaths					
Post county business closure	108.76*	-112.61	-253.58	-249.97	-249.97
	(47.58)	(106.37)	(144.96)	(145.38)	(145.08)
Black/White Segr. index	2.37	0.00	-2.02	0.41	
	(1.46)	(0.00)	(2.43)	(1.47)	
Post county business closure × Black/White Segr. index		4.32	4.25	4.28	4.28
		(2.64)	(2.78)	(2.76)	(2.75)
Observations	2,622	2,622	2,622	2,622	2,622
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column is from a separate regression. Ethnic divisions is measured by the level of racial residential segregation between white and non-white. High and low res. seg. refer to counties with above- and below-median values of the racial residential segregation index, respectively. *Controls* include county-level characteristics (i.e. population density, population size, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, "poor health", diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table A3: Emergency declarations, ethnic fragmentation, and COVID-19 by level of racial segregation (Black vs White)

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
Government policy: National Emergency declaration				
Panel A: Covid-19 cases				
Post Federal emergency declaration	167.65***	702.13***		
	(30.36)	(217.46)		
EFI	459.11***	3649.95**		
	(116.56)	(1370.23)		
Post Federal emergency declaration × EFI			727.80***	5788.31**
			(184.74)	(2174.24)
Observations	146,280	139,242	146,280	139,242
Panel B: Covid-19 deaths				
Post Federal emergency declaration	6.95***	41.42**		
	(1.62)	(15.67)		
EFI	17.05***	228.38**		
	(4.87)	(108.00)		
Post Federal emergency declaration × EFI			27.01***	362.21**
			(7.71)	(171.40)
Observations	146,280	139,242	146,280	139,242
Government policy: County Emergency declaration				
Panel C: Covid-19 cases				
Post county emergency	294.79***	1030.25***	-871.28***	-3359.14***
	(55.55)	(287.40)	(273.38)	(936.63)
EFI	873.46***	4112.05***		
	(227.45)	(1261.37)		
Post county emergency × EFI			1373.90***	6515.25***
			(350.79)	(2054.52)
Observations	44,298	47,886	44,298	47,886
Panel D: Covid-19 deaths				
Post county emergency	11.57***	50.00***	-33.16***	-161.34***
	(2.30)	(14.73)	(10.13)	(49.72)
EFI	33.51***	192.63***		
	(9.06)	(67.71)		
Post county emergency × EFI			53.33***	304.91***
			(14.27)	(109.98)
Observations	44,298	47,886	44,298	47,886
County FE			✓	✓
Day FE			✓	✓

Note: Each column is from a separate regression. High and low res. seg. refer to counties with above- and below-median values of the racial residential segregation index, respectively. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table A4: Other mobility restriction policies, ethnic fragmentation, and COVID-19 by level of racial segregation (Black vs White)

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
Government policy: National Stringency index				
Panel A: Covid-19 cases				
Stringency index	2.59***	10.98***		
	(0.47)	(3.45)		
EFI	429.12***	3477.16**		
	(109.34)	(1322.56)		
Stringency index × EFI			11.20***	90.79**
			(2.85)	(34.55)
Observations	143,100	136,215	143,100	136,215
Panel B: Covid-19 deaths				
Stringency index	0.11***	0.65**		
	(0.03)	(0.25)		
EFI	15.97***	216.85**		
	(4.57)	(103.50)		
Stringency index × EFI			0.42***	5.66**
			(0.12)	(2.71)
Observations	143,100	136,215	143,100	136,215
Government policy: County Safer-at-Home				
Panel C: Covid-19 cases				
Post county safer-at-home order	421.28***	1679.26***	-806.02***	-3826.41***
	(49.51)	(294.95)	(215.05)	(695.74)
EFI	746.47***	3681.56***		
	(180.65)	(585.24)		
Post county safer-at-home order × EFI			1343.75***	6892.65***
			(325.25)	(1105.17)
Observations	10,764	7,866	10,764	7,866
Panel D: Covid-19 deaths				
Post county safer-at-home order	15.12***	60.31***	-26.75***	-145.82***
	(2.94)	(12.76)	(8.13)	(33.25)
EFI	23.56***	130.86***		
	(7.55)	(29.46)		
Post county safer-at-home order × EFI			42.40***	243.84***
			(13.81)	(54.59)
Observations	10,764	7,866	10,764	7,866
Government policy: County Business closure				
Panel E: Covid-19 cases				
Post county business closure	747.15	3470.71**	-4494.71	-5683.93**
	(827.18)	(1164.69)	(6085.53)	(2048.81)
EFI	3908.78	6507.50**		
	(4590.53)	(1810.98)		
Post county business closure × EFI			6629.39	11640.66**
			(9094.36)	(3559.88)
Observations	966	1,656	966	1,656
Panel F: Covid-19 deaths				
Post county business closure	29.84	156.24**	-149.35	-259.26**
	(27.64)	(53.05)	(208.75)	(102.90)
EFI	123.74	313.59**		
	(157.48)	(104.82)		
Post county business closure × EFI			211.30	565.05**
			(313.99)	(201.32)
Observations	966	1,656	966	1,656
County FE			✓	✓
Day FE			✓	✓

Note: Each column is from a separate regression. High and low res. seg. refer to counties with above- and below-median values of the racial residential segregation index, respectively. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table A5: Federal state of emergency, ethnic fragmentation, and Google mobility measures by level of racial segregation (Black vs White)

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
Panel A: Retail				
Post Federal emergency declaration	-13.99***	-13.88***		
	(0.46)	(0.55)		
EFI	4.68***	6.52***		
	(0.91)	(1.13)		
Post Federal emergency declaration × EFI			9.97***	15.84***
			(2.06)	(2.11)
Observations	74,860	89,403	74,858	89,399
Panel B: Grocery				
Post Federal emergency declaration	-2.77***	-4.22***		
	(0.49)	(0.26)		
EFI	-3.50***	-1.22		
	(1.21)	(1.10)		
Post Federal emergency declaration × EFI			2.81	-0.51
			(2.26)	(1.10)
Observations	73,769	85,946	73,766	85,946
Panel C: Parks				
Post Federal emergency declaration	-18.09***	-20.35***		
	(1.72)	(1.37)		
EFI	-7.66**	-1.35		
	(3.00)	(2.32)		
Post Federal emergency declaration × EFI			10.67	-3.02
			(7.29)	(5.04)
Observations	23,655	38,904	23,636	38,869
Panel D: Transit				
Post Federal emergency declaration	-8.46***	-6.73***		
	(0.55)	(0.44)		
EFI	0.13	1.35		
	(1.59)	(1.12)		
Post Federal emergency declaration × EFI			1.84	7.90***
			(2.29)	(2.15)
Observations	40,647	52,345	40,641	52,339
Panel E: Workplace				
Post Federal emergency declaration	-6.39***	-6.50***		
	(0.49)	(0.50)		
EFI	4.70***	6.65***		
	(1.31)	(1.38)		
Post Federal emergency declaration × EFI			11.31***	12.82***
			(1.97)	(2.12)
Observations	97,974	102,171	97,970	102,171
Panel F: Residential				
Post Federal emergency declaration	1.74***	1.80***		
	(0.14)	(0.14)		
EFI	-1.83***	-3.04***		
	(0.33)	(0.29)		
Post Federal emergency declaration × EFI			-2.37***	-3.79***
			(0.62)	(0.44)
Observations	46,486	67,882	46,484	67,880
County FE			✓	✓
Day FE			✓	✓
Controls				

Note: In this table, mobility measures are adjusted for the cumulative number of COVID-19 cases. High and low res. seg. refer to counties with above- and below-median values of the racial residential segregation index, respectively. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table A6: County state of emergency, ethnic fragmentation, and Google mobility measures by level of racial segregation (Black vs White)

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
	Panel A: Retail			
Post county emergency	-10.45***	-10.20***	-8.44***	-8.05***
	(0.76)	(0.67)	(1.74)	(1.49)
EFI	5.54***	5.47***		
	(1.43)	(1.00)		
Post county emergency × EFI			10.98***	16.13***
			(2.69)	(3.08)
Observations	27,693	33,057	27,693	33,054
	Panel B: Grocery			
Post county emergency	-6.41***	-7.12***	-6.07***	-7.20***
	(0.51)	(0.53)	(1.18)	(0.97)
EFI	-2.19*	-0.17		
	(1.27)	(1.00)		
Post county emergency × EFI			4.49**	2.65
			(2.18)	(2.34)
Observations	27,096	32,240	27,096	32,240
	Panel C: Parks			
Post county emergency	-18.44***	-20.19***	-15.31***	-10.40**
	(1.62)	(1.73)	(5.29)	(4.20)
EFI	-5.63	-1.20		
	(4.10)	(3.07)		
Post county emergency × EFI			14.93*	4.30
			(7.73)	(6.74)
Observations	12,794	20,671	12,787	20,663
	Panel D: Transit			
Post county emergency	-7.29***	-5.60***	-9.66***	-8.21***
	(0.44)	(0.55)	(2.40)	(2.48)
EFI	-1.80	2.56*		
	(1.95)	(1.45)		
Post county emergency × EFI			8.54**	7.74*
			(4.05)	(3.98)
Observations	16,704	23,682	16,701	23,678
	Panel E: Workplace			
Post county emergency	-3.08***	-3.68***	-5.90***	-3.75***
	(0.77)	(0.55)	(1.22)	(1.29)
EFI	6.43***	6.95***		
	(1.62)	(1.59)		
Post county emergency × EFI			12.27***	12.06***
			(1.94)	(2.37)
Observations	31,852	35,709	31,852	35,709
	Panel F: Residential			
Post county emergency	0.73***	0.86***	0.95*	0.77**
	(0.17)	(0.12)	(0.47)	(0.34)
EFI	-1.93***	-2.85***		
	(0.46)	(0.27)		
Post county emergency × EFI			-1.98***	-3.14***
			(0.60)	(0.38)
Observations	20,397	27,636	20,396	27,636
County FE			✓	✓
Day FE			✓	✓

Note: In this table, mobility measures are adjusted for the cumulative number of COVID-19 cases. High and low res. seg. refer to counties with above- and below-median values of the racial residential segregation index, respectively. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table A7: Effect of the interaction between emergency declarations and EFI on COVID-19 outcomes by level of racial segregation (White vs non-white)

	Federal state of emergency		County state of emergency	
	Cases (1)	Deaths (2)	Cases (3)	Deaths (4)
Decile 1: Policy × EFI	49.09***	1.59***	60.51**	2.90*
	(13.44)	(0.45)	(26.75)	(1.45)
Observations	42,366	42,366	8,142	8,142
Decile 2: Policy × EFI	140.71***	5.11***	159.58**	8.50**
	(32.66)	(1.11)	(62.85)	(3.19)
Observations	40,434	40,434	12,558	12,558
Decile 3: Policy × EFI	267.30***	7.54***	452.09***	12.86***
	(80.20)	(2.54)	(158.28)	(4.38)
Observations	36,432	36,432	10,902	10,902
Decile 4: Policy × EFI	675.89**	22.30**	1683.36**	55.12**
	(258.77)	(9.52)	(661.71)	(24.98)
Observations	39,054	39,054	11,730	11,730
Decile 5: Policy × EFI	596.29***	22.68**	1140.79***	44.76***
	(215.97)	(8.41)	(391.07)	(14.55)
Observations	37,122	37,122	11,178	11,178
Decile 6: Policy × EFI	1521.93**	76.74**	3566.49**	189.73**
	(584.73)	(37.16)	(1318.97)	(88.36)
Observations	37,398	37,398	11,178	11,178
Decile 7: Policy × EFI	2999.20***	135.15**	3592.47***	139.75**
	(991.99)	(51.71)	(1134.76)	(51.43)
Observations	41,538	41,538	14,904	14,904
Decile 8: Policy × EFI	2160.58*	135.99	2281.14***	76.09**
	(1155.57)	(94.97)	(630.82)	(34.91)
Observations	35,052	35,052	7,038	7,038
Decile 9: Policy × EFI	4444.64**	206.53***	5840.13*	226.16*
	(1684.95)	(73.39)	(3234.35)	(118.71)
Observations	39,882	39,882	12,972	12,972
Decile 10: Policy × EFI	9265.32**	685.23*	9661.22**	515.43*
	(4319.89)	(390.54)	(4317.45)	(253.50)
Observations	35,880	35,880	11,454	11,454
County FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
Policy and EFI Controls	✓	✓	✓	✓

Note: Each row is from a separate regression. The table shows estimates of the effect of the interaction between emergency declarations and EFI on COVID-19 outcomes separately for different deciles of racial residential segregation. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table A8: Effect of EFI on social associations rate by level of racial segregation

	White/non-white Res. Segr.	Black/white Res. Segr.
	(1)	(2)
Dependent variable is Membership in association		
Decile 1: EFI	-2.89	0.80
	(4.43)	(2.46)
Observations	305	210
Decile 2: EFI	0.27	-4.69
	(2.77)	(3.86)
Observations	291	204
Decile 3: EFI	-2.85	0.24
	(2.96)	(1.97)
Observations	257	191
Decile 4: EFI	-1.93	-1.87
	(2.90)	(2.13)
Observations	275	190
Decile 5: EFI	-2.16	-2.14
	(2.44)	(2.15)
Observations	265	224
Decile 6: EFI	0.90	-4.05
	(2.96)	(3.35)
Observations	266	208
Decile 7: EFI	-6.20***	-3.98
	(2.24)	(2.66)
Observations	296	183
Decile 8: EFI	-4.49	0.05
	(3.17)	(2.98)
Observations	247	201
Decile 9: EFI	-4.17	-3.64*
	(2.57)	(1.90)
Observations	282	181
Decile 10: EFI	-4.49	-7.16***
	(2.70)	(2.37)
Observations	252	195
State FE	✓	✓

Note: Each row is from a separate regression. Social associations rate is measured as the number of membership associations per 10,000 individuals in a county. The table shows estimates of the effect of EFI on social associations rate for different deciles of racial residential segregation. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table A9: Cross-correlation table

	(1) EFI	(2) White/non-white Segr. index	(3) Black/White Segr. index
Residual - PCA	0.78	0.96	0.95
Residual	0.73	0.92	0.91
Population density	0.21	0.14	0.12
Percentage of male	0.03	-0.14	-0.05
Average age	-0.42	-0.10	0.02
Poverty	0.25	0.05	-0.20
Education	-0.30	0.09	0.28
Urban area	0.39	0.24	0.28
Immigrants	0.53	0.00	0.07
Poor Health	0.31	0.00	-0.28
Smokers	-0.02	0.14	-0.13
Obesity	0.02	0.02	-0.20
Diabetes	0.05	-0.00	-0.23

Note: This table reports the pairwise correlation coefficient between measures of diversity and divisions (denoted in column headings) and several variables. The variable “Residual” refers to the residual from a fitted regression between the measure denoted in the column heading and the risk factors associated with COVID-19 outcomes including county-level characteristics (i.e. population density, percentage of males, average age, poverty, education, urban/rural classification, and the percentage of immigrants) and county-level health characteristics (i.e. the percentage of adults with obesity, in “poor health”, with diabetes, and who smoke). The variable “Residual-PCA” refers to the residual from a fitted regression between the measure denoted in the column heading and three principal components factors obtained from a Principal Component Analysis using the set of COVID-19 related risk factors listed above.

Appendix B: Analysis of Rates of COVID-19 Cases and Deaths as Dependent Variables

Table B1: Emergency declarations, ethnic fragmentation, and per capita COVID-19 outcomes

	(1)	(2)	(3)	(4)	(5)
Government policy: National Emergency Declaration					
Panel A: Covid-19 cases (per 100,000 individuals)					
Post Federal emergency declaration	140.08***	10.77			
	(14.64)	(16.24)			
EFI	262.45***	0.04**	136.55**	1.28	
	(58.16)	(0.02)	(52.00)	(81.79)	
Post Federal emergency declaration × EFI		416.24***	416.24***	430.48***	416.24***
		(92.25)	(92.27)	(95.53)	(92.27)
Observations	433,596	433,596	433,596	426,696	433,596
Panel B: Covid-19 deaths (per 100,000 individuals)					
Post Federal emergency declaration	5.69***	-0.03			
	(0.95)	(1.00)			
EFI	11.60***		1.68	-3.34	
	(3.49)	(0.00)	(2.95)	(4.12)	
Post Federal emergency declaration × EFI		18.40***	18.40***	19.00***	18.40***
		(5.54)	(5.54)	(5.76)	(5.54)
Observations	433,596	433,596	433,596	426,696	433,596
Government policy: County Emergency Declaration					
Panel C: Covid-19 cases (per 100,000 individuals)					
Post county emergency	156.31***	36.13	-123.65***	-127.73**	-116.75**
	(23.18)	(23.81)	(45.76)	(47.75)	(50.68)
EFI	201.82***	0.13	107.66*	39.27	
	(60.54)	(0.11)	(58.80)	(83.12)	
Post county emergency × EFI		336.88***	347.06***	353.21***	344.61***
		(102.49)	(100.29)	(102.44)	(98.62)
Observations	119,370	119,370	119,370	118,128	119,370
Panel D: Covid-19 deaths (per 100,000 individuals)					
Post county emergency	6.37***	0.79	-6.45***	-6.75***	-6.55***
	(1.28)	(1.12)	(2.30)	(2.34)	(2.27)
EFI	9.38***	0.01*	2.74	0.29	
	(3.32)	(0.01)	(3.28)	(4.38)	
Post county emergency × EFI		15.65***	16.39***	16.51***	16.10***
		(5.62)	(5.61)	(5.73)	(5.56)
Observations	119,370	119,370	119,370	118,128	119,370
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. county area, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p $<$ .001, ** p $<$ .01, * p $<$ .05.

Table B2: Other mobility restriction policies, ethnic fragmentation, and COVID-19 outcomes (rates)

	(1)	(2)	(3)	(4)	(5)
Government policy: National Stringency Index					
Panel A: Covid-19 cases (per 100,000 individuals)					
Stringency index	2.16***	0.17			
	(0.23)	(0.25)			
EFI	245.32***	-53.67***	73.51	-55.02	
	(55.46)	(12.14)	(50.94)	(85.70)	
Stringency index × EFI		6.41***	6.41***	6.63***	6.41***
		(1.45)	(1.45)	(1.50)	(1.45)
Observations	424,170	424,170	424,170	417,420	424,170
Panel B: Covid-19 deaths (per 100,000 individuals)					
Stringency index	0.09***	-			
	(0.01)	(0.02)			
EFI	10.91***	-2.39***	-0.82	-5.64	
	(3.32)	(0.73)	(2.99)	(4.47)	
Stringency index × EFI		0.29***	0.29***	0.29***	0.29***
		(0.09)	(0.09)	(0.09)	(0.09)
Observations	424,170	424,170	424,170	417,420	424,170
Government policy: County Safer-at-Home					
Panel C: Covid-19 cases (per 100,000 individuals)					
Post county safer-at-home order	155.56***	146.45**	-17.14	-20.47	-24.46
	(31.82)	(62.01)	(60.80)	(60.88)	(60.06)
EFI	9.08	-1.42	96.29*	126.85*	
	(57.33)	(1.79)	(54.13)	(62.84)	
Post county safer-at-home order × EFI		19.35	39.87	41.84	42.91
		(103.39)	(96.85)	(97.64)	(96.23)
Observations	20,424	20,424	20,424	20,286	20,424
Panel D: Covid-19 deaths (per 100,000 individuals)					
Post county safer-at-home order	5.09***	4.27*	-1.39	-1.28	-0.94
	(1.13)	(2.40)	(2.44)	(2.56)	(2.51)
EFI	0.98	0.04*	2.52	6.05	
	(2.36)	(0.02)	(1.97)	(3.83)	
Post county safer-at-home order × EFI		1.73	2.55	2.61	2.48
		(4.37)	(4.28)	(4.36)	(4.40)
Observations	20,424	20,424	20,424	20,286	20,424
Government policy: County Business Closure					
Panel E: Covid-19 cases (per 100,000 individuals)					
Post county business closure	234.77***	-83.27	-321.23***	-334.29***	-336.52***
	(54.01)	(64.80)	(82.65)	(84.08)	(84.22)
EFI	430.10***	1.08**	89.07	-90.64	
	(119.04)	(0.45)	(101.81)	(113.72)	
Post county business closure × EFI		781.67***	808.59***	809.25***	813.55***
		(219.64)	(225.97)	(228.51)	(228.76)
Observations	3,726	3,726	3,726	3,726	3,726
Panel F: Covid-19 deaths (per 100,000 individuals)					
Post county business closure	11.01**	-5.81	-18.38***	-18.50***	-18.21***
	(4.46)	(3.25)	(5.06)	(5.13)	(5.04)
EFI	22.70***	0.02*	-3.79	-6.33	
	(6.40)	(0.01)	(7.43)	(7.80)	
Post county business closure × EFI		41.34***	42.89***	42.83***	42.83***
		(11.66)	(11.94)	(12.01)	(11.97)
Observations	3,726	3,726	3,726	3,726	3,726
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. county area, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table B3: Emergency declarations, racial segregation, and per capita COVID-19 outcomes

	(1)	(2)	(3)	(4)	(5)
Government policy: National Emergency Declaration					
Panel A: Covid-19 cases (per 100,000 individuals)					
Post Federal emergency declaration	152.10***	57.61**			
	(15.49)	(23.90)			
White/non-white Segr. index	1.93***		-0.50	-0.70	
	(0.51)	( )	(0.33)	(0.44)	
Post Federal emergency declaration × White/non-white Segr. index		3.07***	3.07***	3.10***	3.07***
		(0.81)	(0.81)	(0.82)	(0.81)
Observations	385,158	385,158	385,158	380,328	385,158
Panel B: Covid-19 deaths (per 100,000 individuals)					
Post Federal emergency declaration	6.26***	0.92			
	(1.01)	(1.28)			
White/non-white Segr. index	0.11***		-0.05*	-0.07**	
	(0.03)	( )	(0.02)	(0.03)	
Post Federal emergency declaration × White/non-white Segr. index		0.17***	0.17***	0.18***	0.17***
		(0.05)	(0.05)	(0.05)	(0.05)
Observations	385,158	385,158	385,158	380,328	385,158
Government policy: County Emergency Declaration					
Panel C: Covid-19 cases (per 100,000 individuals)					
Post county emergency	164.13***	73.61	-67.41	-74.70	-68.67
	(23.39)	(48.75)	(54.19)	(58.82)	(62.30)
White/non-white Segr. index	1.68**	-	-0.14	-0.07	
	(0.77)	( )	(0.50)	(0.69)	
Post county emergency × White/non-white Segr. index		2.84**	2.78**	2.67**	2.68**
		(1.29)	(1.28)	(1.28)	(1.30)
Observations	112,056	112,056	112,056	111,090	112,056
Panel D: Covid-19 deaths (per 100,000 individuals)					
Post county emergency	6.69***	2.07	-4.25	-4.78	-4.70
	(1.28)	(2.87)	(3.26)	(3.42)	(3.49)
White/non-white Segr. index	0.09*	- *	-0.01	-0.04	
	(0.04)	( )	(0.03)	(0.03)	
Post county emergency × White/non-white Segr. index		0.15*	0.14*	0.14*	0.13*
		(0.07)	(0.07)	(0.07)	(0.07)
Observations	112,056	112,056	112,056	111,090	112,056
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. county area, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table B4: Other mobility restriction policies, racial segregation, and per capita COVID-19 outcomes

	(1)	(2)	(3)	(4)	(5)
Government policy: National Stringency Index					
Panel A: Covid-19 cases (per 100,000 individuals)					
Stringency index	2.34***	0.87**			
	(0.24)	(0.37)			
White/non-white Segr. index	1.83***	-0.40***	-0.88**	-1.09**	
	(0.49)	(0.11)	(0.41)	(0.51)	
Stringency index × White/non-white Segr. index		0.05***	0.05***	0.05***	0.05***
		(0.01)	(0.01)	(0.01)	(0.01)
Observations	376,785	376,785	376,785	372,060	376,785
Panel B: Covid-19 deaths (per 100,000 individuals)					
Stringency index	0.10***	0.01			
	(0.02)	(0.02)			
White/non-white Segr. index	0.10***	-0.02***	-0.07**	-0.09**	
	(0.03)	(0.01)	(0.03)	(0.03)	
Stringency index × White/non-white Segr. index		0.00***	0.00***	0.00***	0.00***
		(0.00)	(0.00)	(0.00)	(0.00)
Observations	376,785	376,785	376,785	372,060	376,785
Government policy: County Safer-at-Home					
Panel C: Covid-19 cases (per 100,000 individuals)					
Post county safer-at-home order	156.38***	16.58	-138.98***	-141.06***	-141.50***
	(32.38)	(47.04)	(35.91)	(36.07)	(39.17)
White/non-white Segr. index	2.41***	-0.01	-0.46	-0.85	
	(0.63)	(0.02)	(0.56)	(0.65)	
Post county safer-at-home order × White/non-white Segr. index		4.47***	4.50***	4.47***	4.44***
		(1.12)	(1.12)	(1.11)	(1.12)
Observations	20,286	20,286	20,286	20,148	20,286
Panel D: Covid-19 deaths (per 100,000 individuals)					
Post county safer-at-home order	5.13***	1.14	-4.12*	-3.99*	-3.57*
	(1.15)	(2.42)	(2.08)	(2.02)	(2.03)
White/non-white Segr. index	0.07*	-	-0.01	-0.02	
	(0.03)	(0.00)	(0.03)	(0.03)	
Post county safer-at-home order × White/non-white Segr. index		0.13*	0.13*	0.12*	0.12*
		(0.06)	(0.06)	(0.06)	(0.06)
Observations	20,286	20,286	20,286	20,148	20,286
Government policy: County Business Closure					
Panel E: Covid-19 cases (per 100,000 individuals)					
Post county business closure	252.86***	-96.21	-358.99***	-351.84***	-349.26***
	(45.71)	(79.24)	(75.73)	(84.77)	(83.93)
White/non-white Segr. index	5.37***	0.01	-0.45	-5.07***	
	(0.98)	(0.01)	(0.68)	(1.02)	
Post county business closure × White/non-white Segr. index		10.00***	10.06***	10.04***	10.04***
		(1.81)	(1.80)	(1.77)	(1.77)
Observations	3,450	3,450	3,450	3,450	3,450
Panel F: Covid-19 deaths (per 100,000 individuals)					
Post county business closure	11.94**	0.09	-13.51**	-12.56**	-12.30**
	(4.15)	(6.29)	(4.90)	(4.97)	(4.95)
White/non-white Segr. index	0.18**		-0.06	-0.31***	
	(0.07)	(0.00)	(0.05)	(0.08)	
Post county business closure × White/non-white Segr. index		0.34**	0.34**	0.34**	0.34**
		(0.13)	(0.13)	(0.13)	(0.13)
Observations	3,450	3,450	3,450	3,450	3,450
State FE			✓	✓	
County FE					✓
Day FE			✓	✓	✓
Controls				✓	

Note: Each column of each panel reports coefficients from a separate regression. The dependent variable in each regression is denoted by the corresponding panel title. *Controls* include county-level demographic characteristics (i.e. county area, percentage of males, average age, poverty, education, urban area, the percentage of immigrants, share of Trump voters) and county-level health characteristics (i.e. the percentage of adults with obesity, in "poor health", with diabetes, and who smoke). Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table B5: Emergency declarations, ethnic fragmentation, and per capita COVID-19 by level of white/non-white racial segregation

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
Government policy: National Emergency declaration				
Panel A: Covid-19 cases (per 100,000 individuals)				
Post Federal emergency declaration	115.36***	189.94***		
	(14.70)	(21.39)		
EFI	198.07***	351.58***		
	(47.92)	(86.77)		
Post Federal emergency declaration × EFI			314.14***	557.60***
			(76.04)	(137.67)
Observations	195,408	189,750	195,408	189,750
Panel B: Covid-19 deaths (per 100,000 individuals)				
Post Federal emergency declaration	4.24***	8.35***		
	(0.80)	(1.47)		
EFI	6.44***	17.68***		
	(2.33)	(5.71)		
Post Federal emergency declaration × EFI			10.22***	28.04***
			(3.69)	(9.06)
Observations	195,408	189,750	195,408	189,750
Government policy: County Emergency declaration				
Panel C: Covid-19 cases (per 100,000 individuals)				
Post county emergency	129.03***	195.86***	-67.05**	-153.16*
	(29.62)	(27.77)	(29.69)	(89.28)
EFI	155.94**	236.32***		
	(68.08)	(86.26)		
Post county emergency × EFI			282.76**	397.49***
			(119.78)	(141.66)
Observations	54,510	57,546	54,510	57,546
Panel D: Covid-19 deaths (per 100,000 individuals)				
Post county emergency	5.21**	8.01***	-2.29	-10.58***
	(1.94)	(1.31)	(1.61)	(3.63)
EFI	6.77	11.30**		
	(4.33)	(4.25)		
Post county emergency × EFI			12.40	19.06***
			(7.76)	(6.87)
Observations	54,510	57,546	54,510	57,546
County FE			✓	✓
Day FE			✓	✓

Note: Each column of each panel reports coefficients from a separate regression. "High res. seg." and "Low res. seg." refer to regressions limited to counties with above- and below-median values of racial residential segregation, respectively. The dependent variable in each regression is denoted by the corresponding panel title. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table B6: Other mobility restriction policies, ethnic fragmentation, and per capita COVID-19 by level of White/non-White racial segregation

	Low res. seg. (1)	High res. seg. (2)	Low res. seg. (3)	High res. seg. (4)
Government policy: National Stringency index				
Panel A: Covid-19 cases (per 100,000 individuals)				
Stringency index	1.77***	2.93***		
	(0.23)	(0.34)		
EFI	182.06***	331.69***		
	(44.91)	(83.55)		
Stringency index × EFI			4.76***	8.66***
			(1.17)	(2.18)
Observations	191,160	185,625	191,160	185,625
Panel B: Covid-19 deaths (per 100,000 individuals)				
Stringency index	0.07***	0.13***		
	(0.01)	(0.02)		
EFI	6.01***	16.70***		
	(2.19)	(5.45)		
Stringency index × EFI			0.16***	0.44***
			(0.06)	(0.14)
Observations	191,160	185,625	191,160	185,625
Government policy: County Safer-at-Home				
Panel C: Covid-19 cases (per 100,000 individuals)				
Post county safer-at-home order	134.54**	177.87***	-25.22	-4.75
	(41.44)	(32.65)	(83.58)	(63.01)
EFI	-1.81	-3.31		
	(90.35)	(62.11)		
Post county safer-at-home order × EFI			24.76	22.15
			(158.78)	(102.48)
Observations	10,074	10,212	10,074	10,212
Panel D: Covid-19 deaths (per 100,000 individuals)				
Post county safer-at-home order	4.25***	5.99***	-0.49	-0.71
	(1.24)	(1.41)	(2.59)	(4.02)
EFI	1.00	0.17		
	(2.48)	(3.73)		
Post county safer-at-home order × EFI			2.34	1.27
			(4.78)	(7.00)
Observations	10,074	10,212	10,074	10,212
Government policy: County Business closure				
Panel E: Covid-19 cases (per 100,000 individuals)				
Post county business closure	165.20	310.15***	-249.19*	-462.45**
	(89.27)	(56.95)	(95.47)	(193.09)
EFI	424.40***	483.45**		
	(34.55)	(200.31)		
Post county business closure × EFI			772.05***	955.16**
			(95.91)	(405.14)
Observations	1,380	2,070	1,380	2,070
Panel F: Covid-19 deaths (per 100,000 individuals)				
Post county business closure	8.92	13.92***	-19.68	-22.50*
	(7.26)	(3.91)	(9.78)	(11.13)
EFI	36.18***	22.11*		
	(6.19)	(10.04)		
Post county business closure × EFI			66.25**	43.84*
			(12.63)	(19.76)
Observations	1,380	2,070	1,380	2,070
County FE			✓	✓
Day FE			✓	✓

Note: Each column of each panel reports coefficients from a separate regression. "High res. seg." and "Low res. seg." refer to regressions limited to counties with above- and below-median values of racial residential segregation, respectively. The dependent variable in each regression is denoted by the corresponding panel title. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.

Table B7: Effect of the interaction between emergency declarations and EFI on per capita COVID-19 outcomes by level of white/non-white racial segregation

	Federal state of emergency		County state of emergency	
	Cases (1)	Deaths (2)	Cases (3)	Deaths (4)
Decile 1: Policy × EFI	145.14***	5.23***	153.44*	5.58
	(40.78)	(1.83)	(86.71)	(4.27)
Observations	42,366	42,366	8,142	8,142
Decile 2: Policy × EFI	132.23***	4.07**	49.06	2.40
	(45.15)	(1.62)	(29.59)	(1.93)
Observations	40,434	40,434	12,558	12,558
Decile 3: Policy × EFI	170.42**	3.57	126.61	4.21
	(66.40)	(2.15)	(76.92)	(2.75)
Observations	36,432	36,432	10,902	10,902
Decile 4: Policy × EFI	159.61**	4.83*	196.00**	6.52
	(63.30)	(2.66)	(78.04)	(5.38)
Observations	39,054	39,054	11,730	11,730
Decile 5: Policy × EFI	140.16***	5.23**	102.52*	4.70
	(48.84)	(2.49)	(56.88)	(4.52)
Observations	37,122	37,122	11,178	11,178
Decile 6: Policy × EFI	173.05***	7.96***	204.68**	9.33
	(38.33)	(2.46)	(85.02)	(6.16)
Observations	37,398	37,398	11,178	11,178
Decile 7: Policy × EFI	145.12**	6.66	-15.35	-3.95
	(66.55)	(4.21)	(91.55)	(4.43)
Observations	41,538	41,538	14,904	14,904
Decile 8: Policy × EFI	231.96***	13.66*	149.01**	5.88
	(78.68)	(6.81)	(66.14)	(4.51)
Observations	35,052	35,052	7,038	7,038
Decile 9: Policy × EFI	453.44***	19.63***	300.72**	11.04*
	(121.87)	(5.64)	(138.93)	(5.87)
Observations	39,882	39,882	12,972	12,972
Decile 10: Policy × EFI	341.59***	18.80**	355.07***	17.46**
	(84.19)	(7.42)	(104.51)	(6.66)
Observations	35,880	35,880	11,454	11,454
County FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
Policy and EFI Controls	✓	✓	✓	✓

Note: Each row is from a separate regression. The table shows estimates of the effect of the interaction between emergency declarations and EFI on COVID-19 outcomes separately for different deciles of racial residential segregation. Standard errors are clustered at the state level. ***p < .001, ** p < .01, * p < .05.