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Nonlinear Effects of Mobility on COVID-19 in the U.S.: Targeted Lockdowns Based on Income and Poverty

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Abstract

This paper investigates nonlinearities in the relationship between mobility and COVID-19 cases or deaths. The formal analysis is achieved by using county-level daily data from the U.S., where a difference-in-difference design is employed. Nonlinearities in the relationship between mobility and COVID-19 cases or deaths are investigated by regressing weekly percentage changes in COVID-19 cases or deaths on mobility measures, where county fixed effects and daily fixed effects are controlled for. The main innovation is achieved by distinguishing between the coefficients in front of mobility measures across U.S. counties based on their demographic or socioeconomic characteristics. The results suggest that the positive effects of mobility on COVID-19 cases or deaths increase with population, per capita income, or commuting time as well as with having certain occupations, working in certain industries, attending certain schools, or having certain educational attainments. Important policy implications follow regarding where mobility restrictions would work better to fight against COVID-19 through targeted lockdowns.

Keywords: Coronavirus; COVID-19; Mobility; Demographics; Lockdowns

JEL Classification: I10, I18

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1. Introduction

The positive relationship between the spread of COVID-19 and social interactions through mobility is well established (Yilmazkuday, 2020b; Yilmazkuday, 2021a). Based on this relationship, several governments have employed lockdowns to slow down the spread of COVID-19. However, this relationship by itself does not suggest anything related to targeted lockdowns that can be useful when policy makers face trade-offs between health-related concerns and economic slowdown as certain group of people or certain communities can be more vulnerable to the spread of COVID-19.

Based on this motivation, this paper investigates how the relationship between mobility and the COVID-19 spread changes with demographic or socioeconomic characteristics, including income and poverty. The formal investigation is achieved by using daily county-level data from the U.S., where a difference-in-difference approach is employed. The nonlinear relationship between mobility and COVID-19 cases or deaths is investigated by regressing weekly percentage changes in COVID-19 cases or deaths on mobility measures, where county fixed effects and daily fixed effects are included; accordingly, county-specific factors that are constant over time and day-specific factors that are common across U.S. counties are already controlled for. The main contribution of the paper is achieved by distinguishing between the coefficients in front of mobility measures across U.S. counties based on their demographic or socioeconomic characteristics that we utilize as threshold variables.

Several demographic or socioeconomic characteristics of U.S. counties are considered for investigating the nonlinear relationship between mobility and the COVID-19 spread. These include 45 different variables based on the categories of population characteristics, economic variables, occupations, employment in industries, school attendance, educational attainment, and race. The motivation behind including these potential threshold variables comes from the existing literature, where several studies have shown how the spread of COVID-19 is related to these demographic or socioeconomic characteristics (to be discussed more, below).

The results of the nonlinear investigation suggest that the positive effects of mobility on COVID-19 cases or deaths increase with poverty, per capita income, commuting time or population, as well as with having certain occupations, working in certain industries, attending certain schools, or having certain educational attainments. Since mobility restrictions to fight against COVID-19 would work better in counties where the positive effects of mobility on COVID-19 cases or deaths are bigger, it is implied that policy makers can consider targeted lockdowns based on the threshold variables identified in this paper.

The rest of the paper is organized as follows. The next section reviews the existing literature. Section 3 introduces the formal estimation methodology used. Section 4 introduces the data set. Section 5 depicts empirical results. Section 6 discusses the empirical results to the existing literature. Section 7 concludes.

2. Literature Review

This section reviews the existing literature on the spread of COVID-19 and the mobility of individuals, where the role of demographic and socioeconomic variables, including income and poverty, is investigated. The contribution of this paper with respect to different strands of the literature is also discussed.

The literature has shown a positive relationship between mobility of individuals and the spread of COVID-19. Among others, (Yilmazkuday, 2021a) has shown by using mobility data covering 130 countries that spending more time outside of residential locations increases both COVID-19 cases and deaths, whereas staying at home has the opposite effect. Similarly, (Yilmazkuday, 2020b) has shown that lower inter-county travel within the U.S. is associated with lower COVID-19 cases and deaths. However, this literature is silent about the different magnitudes of the positive relationship across alternative demographic or socioeconomic groups, which is the key question in this paper.

A strand of the literature has shown evidence for unequal mobility changes across demographic and socioeconomic groups amid COVID-19, which may be effective on the spread of COVID-19. Among others, (Aromí et al., 2020) have shown that higher socioeconomic status is associated with more intense reductions in mobility based on data from 8 large Latin American urban areas. Similarly, (Yilmazkuday, 2020a) has shown evidence for lower-income and lower-educated people in the U.S. experiencing relatively less social distancing amid COVID-19. Finally, (Yechezkel et al., 2021) have shown that lower-income regions in Israel have exhibited lower and slower compliance with the restrictions related to COVID-19. However, these studies are about explaining the difference in the mobility of demographic and socioeconomic groups rather than the different effects of mobility on the spread of COVID-19 through these groups (which is the focus of this paper).

There is another part of the literature that focuses on the relationship between the spread of COVID-19 and population demographics. Among others, (Kadi & Khelfaoui, 2020; Rubin et al., 2020; Stojkoski et al., 2020; Sy et al., 2021) have shown a positive correlation between population density and the spread of COVID-19, whereas (Lau et al., 2020; Li & Mutchler, 2020) have shown that age is an important factor in the spread of COVID-19. Other studies such as by (Andersen et al., 2020; Bui et al., 2020; Holmes et al., 2020; Jay et al., 2020; McLaren, 2020; Muñoz-Price et al., 2020; Ristovska, 2021) have shown evidence of certain race groups (of Blacks and Hispanics) getting infected more compared to others. However, these studies do not investigate how mobility interacts with these population demographics to explain the spread of COVID-19 in a nonlinear way (as this paper does).

Economic factors have also been shown to be effective in explaining the spread of COVID-19 in the literature. For example, (Brown & Ravallion, 2020) have shown that the COVID-19 spread increases with poverty and inequality across U.S. counties. Similarly, (Mukherji, 2020) has shown that the COVID-19 spread has been faster in U.S. counties with higher income inequality. In another study, (Baena-Díez et al., 2020) have shown that districts of Barcelona (Spain) with the lowest income have experienced the highest spread of COVID-19. (Bui et al., 2020) have shown that people working in certain sectors of manufacturing, construction and wholesale trade in the State of Utah have experienced the highest levels of COVID-19 spread. However, these studies do not investigate the nonlinear relationship between mobility and the spread of COVID-19 that interacts with these economic factors (as it is done in this paper).

Another stand of the literature has investigated the welfare implications of COVID-19 by focusing on the spread of the disease, the economic implications, or both. Among others, (Yilmazkuday, 2021c) has introduced an economic model, where individuals decide on their mobility to maximize their welfare that depends on the trade-off between consumption (requiring mobility) and the spread of COVID-19 (caused by mobility). Combining this model with the U.S. county-level data, he has shown evidence for about 11% of a reduction in welfare during 2020 for the average U.S. county; these welfare reductions have been higher in the U.S. counties with higher shares of Asian or Hispanic/Latino population. In another study, (Yilmazkuday, 2021d) has investigated the welfare costs of individuals in the U.S. due to the reduction in their travel behavior during COVID-19. He has shown that the cumulative welfare costs of reduced travel with respect to January 20th, 2020 is about 11% as of April 19th, 2020 within the U.S., with a range between 7% and 16% across U.S. counties. Finally, (Yilmazkuday, 2021b) has shown evidence for unequal welfare costs of staying at home across demographic and socioeconomic groups, where the average (across days) welfare costs have been experienced the most by the Asian population, followed by the Hispanic population, the white population, the black population and the native population. Despite providing highly useful welfare implications, these studies do not investigate the nonlinear relationship between mobility and the spready of COVID-19 (based on demographic and socioeconomic groups), and, thus, they cannot provide any policy suggestions regarding targeted lockdowns (as this paper does).

Overall, the existing literature either focuses on the relationship between the spread of COVID-19 and demographic/socioeconomic characteristics or the relationship between mobility and demographic/socioeconomic characteristics. In contrast, this paper focuses on the nonlinear relationship between the spread of COVID-19 and mobility that interacts with these demographic or socioeconomic characteristics.

3. Estimation Methodology

This section introduces the estimation methodology used to investigate the relationship between mobility and COVID-19 cases or deaths. The investigation starts with a linear framework, where the effects of mobility on COVID-19 cases or deaths are common across U.S. counties. The investigation continues with a nonlinear framework, where the effects of mobility on COVID-19 cases or deaths are distinguished across U.S. counties based on their demographic or socioeconomic characteristics.

All regressions are based on a difference-in-difference design, where county fixed effects and day fixed effects are controlled for. The weekly percentage changes in COVID-19 cases or deaths correspond to continuous treatments in the difference-in-difference design. In these regressions, percentage changes (measured as log changes over time) in COVID-19 cases or deaths (per 100,000 people) are considered to ensure that the investigation is independent of any scale issues.

3.1. Linear Framework

The linear effects of mobility on COVID-19 cases are investigated by considering a unique coefficient in front of mobility in regressions. Specifically, the formal investigation regarding the linear effects of mobility on COVID-19 cases is achieved by using the following expression:

$$\Delta S_{c,t} = \beta_0 + \beta_1 \Delta M_{c,t-21} + \theta_c + \gamma_t + \varepsilon_{c,t} \tag{1}$$

where $\Delta S_{c,t}$ represents the weekly percentage change in cumulative daily COVID-19 cases in county c at day t, and $\Delta M_{c,t-21}$ represents the lagged change in mobility (measured by time spent away from home) in county c at day $t-21$ with respect to the pre-COVID-19 period. The lagged change in mobility is used to consider the time delay that is necessary for the effects of mobility to show up on COVID-19 cases.

In Equation (1), county-fixed effects are represented by θ_c's. Specifically, θ_c's represent county-specific dummy variables that take a value of 1 for county c and a value of zero for other countries. The inclusion of these fixed effects ensures that county-specific factors that are constant over time (e.g., any demographic or socioeconomic factor as a potential additional right-hand-side variable) are controlled for during the investigation.

In Equation (1), day-fixed effects are represented by γ_t's. Specifically, γ_t's represent day-specific dummy variables that take a value of 1 for day t and a value of zero for other days. The inclusion of these fixed effects ensures that day-specific factors that are common across countries (e.g., declaration of a National Emergency concerning COVID-19 on March 13th, 2020 by the White House) are controlled for during the investigation. Finally, $\varepsilon_{c,t}$ represents residuals.

Similarly, the formal investigation regarding the linear effects of mobility on COVID-19 deaths is achieved by using the following expression:

$$\Delta V_{c,t} = \beta_0 + \beta_1 \Delta M_{c,t-35} + \theta_c + \gamma_t + \varepsilon_{c,t} \qquad (2)$$

where $\Delta V_{c,t}$ represents the weekly percentage change in cumulative daily

COVID-19 deaths in county c at day t, and $\Delta M_{c,t-35}$ represents the lagged change in mobility (measured by time spent away from home) in county c at day $t-35$ with respect to the pre-COVID-19 period. The lagged change in mobility is used to consider the time delay that is necessary for the effects of mobility to show up on COVID-19 deaths (which is two weeks longer compared to COVID-19 cases); this is also essential to consider the causality through the time dimension in our regressions. Other variables are the same as in Equation (1).

3.2. Nonlinear Framework

The relationship between mobility and the spread of COVID-19 that is represented by the coefficient in front of mobility in Equations (1) and (2) can be affected by several demographic or socioeconomic factors. This can be motivated by the studies in the existing literature that show evidence for the spread of COVID-19 depending on these factors. Accordingly, this subsection introduces a methodology for distinguishing between the coefficients in front of mobility for alternative demographic or socioeconomic factors, which can be achieved by using an interaction dummy based on these factors.

Considering interaction dummies based on population characteristics in the nonlinear investigation is in line with earlier studies in the literature that have provided evidence for the relationship between the spread of COVID-19 and variables such as population density, age, or family size (Kadi & Khelfaoui, 2020; Lau et al., 2020; Li & Mutchler, 2020; Rubin et al., 2020; Stojkoski et al., 2020; Sy et al., 2021).

Regarding economic variables, earlies studies have shown how the spread of COVID-19 is associated with income, poverty, having health insurance or the length of commuting time (Baena-Díez et al., 2020; Brown & Ravallion, 2020; Ehlert, 2021; Hawkins et al., 2020; Jay et al., 2020; Karaye & Horney, 2020; Maness et al., 2021; Mukherji, 2020; Stojkoski et al., 2020; Tavares & Betti, 2021). Accordingly, we also consider these variables as potential determinants of nonlinearities.

Certain occupations, employment in certain industries or educational attainment also determine the potential social distancing of individuals in their workplaces (Bui et al., 2020; Figueroa et al., 2020). Therefore, we also consider the heterogeneity of U.S. counties regarding these characteristics while investigating the nonlinear relationship between mobility and the spread of COVID-19.

Similarly, being members of a particular race or attending to alternative schools may also alter the spread of COVID-19 (Andersen et al., 2020; Bui et al., 2020; Holmes et al., 2020; Jay et al., 2020; McLaren, 2020; Muñoz-Price et al., 2020; Ristovska, 2021). Hence, we also consider the corresponding variables as potential determinants of nonlinearity.

Based on the motivation obtained from these earlier studies, the nonlinear effects of mobility on COVID-19 cases are investigated by distinguishing between the coefficients in front of mobility across U.S. counties, where an interaction dummy variable based on demographic and socioeconomic factors is used. Specifically, the formal investigation regarding the nonlinear effects of mobility on COVID-19 cases is achieved by using the following expression:

$$\Delta S_{c,t} = \beta_0 + \beta_1 D_c \Delta M_{c,t-21} + \beta_2 (1 - D_c) \Delta M_{c,t-21} + \theta_c + \gamma_t + \varepsilon_{c,t} \tag{3}$$

where the only difference with respect to Equation (1) is having a dummy variable of D_c that takes a value of 1 if a threshold variable of interest (e.g., population) in county c is below its median value across counties and 0 otherwise. Individual regressions are run for each threshold variable.

Similarly, the formal investigation regarding the nonlinear effects of mobility on COVID-19 deaths is achieved by using the following expression:

$$\Delta V_{c,t} = \beta_0 + \beta_1 D_c \Delta M_{c,t-35} + \beta_2 (1 - D_c) \Delta M_{c,t-35} + \theta_c + \gamma_t + \varepsilon_{c,t} \tag{4}$$

where the only difference with respect to Equation (2) is having a dummy variable of D_c that takes a value of 1 if a threshold variable of interest (e.g., population) in county c is below its median value across counties and 0 otherwise.

Individual regressions are run for each threshold variable. It is important to emphasize that county-specific dummy variables in Equations (3) and (4) already control for any county-specific factors that are constant over time, including any demographic or socioeconomic factor as a potential additional right-hand-side variable. This confirms one more time that the focus of this paper is on the relationship between mobility and the spread of COVID-19 based on the corresponding coefficient of mobility in our regressions rather than demographic or socioeconomic factors as additional right-hand-side variables.

4. Data and Variables

Daily U.S. county-level COVID-19 cases and deaths that are used in the estimation of Equations (1), (2), (3) and (4) are obtained from Opportunity

Insights Economic Tracker (OIET), and they are measured by confirmed COVID-19 cases and deaths per 100,000 people, seven day moving average.[2] Daily U.S. county-level mobility data are also obtained from OIET, and they are measured by the time spent outside of residential locations relative to the period between January 3 and February 6, 2020.[3] The sample covers the daily period between February 24 and December 13, 2020.

The corresponding descriptive statistics are given in the Appendix Table A.1, where statistics based on the pooled sample across U.S. counties and days are presented. As is evident, there is a significant amount of heterogeneity across U.S. counties and days regarding the COVID-19 cases and deaths. The mobility of individuals (measured by the time spent outside of residential locations) is also highly different across U.S. counties and days during the sample period, when the average mobility has decreased about 8.48% with respect to period between January 3 and February 6, 2020, with a standard deviation of about 6.15%. It is implied that both mobility and the spread of COVID-19 have been experienced differently across U.S. counties and days, which motivates the focus on this paper based on targeted lockdowns.

The correlation between the spread of COVID-19 and mobility is also given in the Appendix Table A.1, where the correlation coefficients are again based on the pooled sample across U.S. counties and days. As is evident, CCOVID-19 cases are highly correlated to deaths (as expected). Mobility is also highly correlated with both COVID-19 cases and deaths, consistent with earlier studies such as by (Yilmazkuday, 2021a).

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[2] OIET obtains this information from New York Times COVID-19 repository.

[3] OIET obtains this information from Google.

Demographic or socioeconomic characteristics of U.S. counties that are used in the estimation of Equations (3) and (4) are obtained from American Community Survey covering the 5-year estimates between 2014-2018.[4] These include 45 threshold variables based on the categories of population characteristics, economic variables, occupations, employment in industries, school attendance, educational attainment, and race. The corresponding variables in each category can be found in the tables representing the estimation results, below.

5. Estimation Results

This section depicts the estimation results based on linear and nonlinear regressions introduced above. Linear regressions are based on Equations (1) and (2), whereas nonlinear regressions are based on Equations (3) and (4). Individual regressions are run for each threshold variable in nonlinear regressions.

5.1. Linear Regressions

Estimation results based on Equations (1) and (2) are given in Table 1. As is evident, 1% of an increase in lagged mobility results in about 0.94% of an increase in COVID-19 cases and about 0.41% of an increase in COVID-19 deaths. It is implied that the linear effects of mobility on COVID-19 are positive and significant. This result is robust to the consideration of day fixed effects and county fixed effects.

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[4] The webpage is https://www.census.gov/programs-surveys/acs/data/summary-file.html.

5.2. Nonlinearities through Population Demographics

Estimation results based on the nonlinear effects of mobility on COVID-19 through population demographics are given in Table 2, where the estimates in columns titled "Below Median" and "Above Median" represent the coefficient of mobility when the population demographic variable is below and above its median value, respectively. The difference between these two coefficients is represented in columns titled "Difference" of which significance can be used to confirm the existence of a nonlinear relationship between mobility and COVID-19 cases or deaths.

As is evident, the positive effects of mobility on COVID-19 cases are significantly bigger in U.S. counties that are more populated. The effects of mobility on COVID-19 deaths are negative (positive) for counties that are populated below (above) the median county.

The positive effects of mobility on COVID-19 cases increase with the average family size, the median age or the percentage of people who are older than 65 years, although the corresponding differences across counties are not statistically significant when COVID-19 deaths are considered. Finally, the positive effects of mobility on COVID-19 cases or deaths decrease with the percentage of grandparents responsible for grandchildren. It is implied that the results based on family size or age are mixed.

Overall, when both COVID-19 cases and deaths are considered for robustness, total population is the only variable (among the threshold variables considered in Table 2) that clearly leads into significant differences across U.S. counties regarding the effects of mobility on COVID-19. It is implied that mobility restrictions to fight against COVID-19 would work better in more populated counties.

5.3. Nonlinearities through Economic Variables

Estimation results based on the nonlinear effects of mobility on COVID-19 through economic variables are given in Table 3. Both COVID-19 cases and deaths increase more with mobility when per capita income goes up, whereas they increase less with mobility when median household income goes up. The positive effects of mobility on COVID-19 cases increase with poverty, however those on COVID-19 deaths go down with poverty. The positive effects of mobility on COVID-19 cases decrease with the percentage of people having health insurance, however the difference is insignificant when COVID-19 deaths are considered. Finally, the positive effects of mobility on COVID-19 cases and deaths increase with commuting time.

Overall, when both COVID-19 cases and deaths are considered for robustness, per capita income and commuting time (among the threshold variables considered in Table 3) are the only variables that clearly result in significantly bigger positive effects of mobility on COVID-19. It is implied that mobility restrictions to fight against COVID-19 would work better in counties with higher per capita income or longer commuting times.

5.4. Nonlinearities through Occupations

Estimation results based on the nonlinear effects of mobility on COVID-19 through occupations are given in Table 4. When both COVID-19 cases and deaths are considered for robustness, the positive effects of mobility significantly increase with management, business, science, and arts occupations as well as service occupations, whereas they significantly decrease with natural resources, construction, and maintenance occupations as well as production, transportation, and material moving occupations. It is implied that mobility restrictions to fight against COVID-19 would work better in counties with higher shares of management, business, science, and arts occupations as well as service occupations.

5.5. Nonlinearities through Employment in Industries

Estimation results based on the nonlinear effects of mobility on COVID-19 through employment in industries are given in Table 5. When both COVID-19 cases and deaths are considered for robustness, the positive effects of mobility significantly increase with employment in transportation and warehousing, and utilities, information, finance and insurance, and real estate and rental and leasing, professional, scientific, and management, or administrative and waste management services, educational services, and health care and social assistance. It is implied that mobility restrictions to fight against COVID-19 would work better in counties where people are employed more in such industries.

5.6. Nonlinearities through School Attendance

Estimation results based on the nonlinear effects of mobility on COVID-19 through school attendance are given in Table 6. When both COVID-19 cases and deaths are considered for robustness, the positive effects of mobility significantly increase with attendance to nursery school, preschool as well as college or graduate school. It is implied that mobility restrictions to fight against COVID-19 would work better in counties where students attend more to these schools.

5.7. Nonlinearities through Educational Attainment

Estimation results based on the nonlinear effects of mobility on COVID-19 through educational attainment are given in Table 7. When both COVID-19 cases and deaths are considered for robustness, the positive effects of mobility significantly increase with bachelor's degree as well as graduate or professional degree. It is implied that mobility restrictions to fight against COVID-19 would work better in counties where more individuals have a bachelor's or a higher degree.

5.8. Nonlinearities through Race

Estimation results based on the nonlinear effects of mobility on COVID-19 through race are given in Table 8. When both COVID-19 cases and deaths are considered for robustness, there are no significant differences across counties regarding the effects of mobility on COVID-19 cases or deaths. It is implied that factors other than race (that have been covered so far) are more important determinants of such effects.

6. Discussion of Results

This section provides economic intuition for the estimation results by connecting them to the existing literature.

The estimation results suggesting that the positive effects of mobility on

COVID-19 cases or deaths increase with total population are consistent with the idea that the degree of disease spread scales proportionally with population density. Although earlier studies such as by (Kadi & Khelfaoui, 2020; Rubin et al., 2020; Stojkoski et al., 2020) have shown a positive relationship between population density and COVID-19 spread, it is important to emphasize that the ingredients of these papers are captured by county-fixed effects in this paper. Accordingly, the contribution of this paper is rather through showing how population can stimulate the positive effects of mobility on COVID-19 cases or deaths.

The estimation results showing that the positive effects of mobility on COVID-19 cases or deaths increase with per capita income or commuting time suggest that higher economic activity or the corresponding social interactions can increase the spread of COVID-19 through mobility. This is consistent with earlier studies such as by (Yang et al., 2020) or (McLaren, 2020) who have shown how commuting time or using public transit can stimulate the spread of COVID-19.

The positive effects of mobility on COVID-19 significantly increasing with certain occupations, employment in certain industries or certain educational attainment can be explained by the corresponding social interactions associated with these occupations or education levels. Specifically, occupations (based on alternative education levels) that are usually achieved with relatively less social distancing in closed spaces (e.g., management, sales, health care, accommodation) may be leading into higher spread of COVID-19 compared to other occupations. This is consistent with earlier studies such as by (Figueroa et al., 2020) or (Bui et al., 2020) who have shown how the COVID-19 spread can be different across alternative occupations. It is implied that policies that would mitigate the spread of COVID-19 in certain occupations, including mask mandates as consistent with studies such as by (Yilmazkuday, 2020c), would be helpful to reduce the inequality created by the pandemic.

Similarly, the positive effects of mobility on COVID-19 significantly increasing with attendance to preschool and college or graduate school can be explained by either the social distancing that is achieved by these age groups or the closures of other schools as indicated in studies such as by (Jay et al., 2020) or (Andersen et al., 2020).

Overall, the positive effects of mobility on COVID-19 cases or deaths increase with population, per capita income, or commuting time as well as with having certain occupations, working in certain industries, attending certain schools, or having certain educational attainments. It is implied that mobility restrictions to fight against COVID-19 would work better in counties where the positive effects of mobility on COVID-19 cases or deaths are bigger. Therefore, policy makers can consider targeted lockdowns based on the threshold variables identified in this paper, consistent with earlier studies such as by (Acemoglu et al., 2020) who have suggested using targeted policies.

7. Conclusion

This paper has investigated the relationship between mobility and the COVID-19 spread by using county-level daily data from the U.S., where a difference-in-difference design has been employed. Nonlinearities in the relationship between mobility and COVID-19 cases or deaths have been investigated by regressing weekly percentage changes in COVID-19 cases or deaths on mobility measures, where county fixed effects and daily fixed effects are controlled for. The main innovation has been achieved by distinguishing between the coefficients in front of mobility measures across U.S. counties based on their demographic or socioeconomic characteristics.

The estimation results have suggested that the positive effects of mobility on COVID-19 cases or deaths increase with poverty, per capita income, commuting time or population, as well as with having certain occupations, working in certain industries, attending certain schools, or having certain educational attainments. Since mobility restrictions to fight against COVID-19 would work better in counties with bigger positive effects of mobility on COVID-19 cases or deaths, it is implied that policy makers can consider targeted lockdowns based on the threshold variables identified in this paper.

As the spread of COVID-19 comes together with a reduction in economic activity and thus welfare of individuals as shown in studies such as by (Yilmazkuday, 2021c), having targeted lockdowns can be compensated in monetary terms especially in U.S. counties with higher poverty, higher commuting time, higher population, higher age, higher family size, higher shares of occupations that require being at the workplace, higher shares of college students, or higher shares of Black population. This is important not only to mitigate the negative effects of COVID-19 on the economic activity and thus poverty but also to mitigate the economic inequality across individuals created by COVID-19.

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Table 1 - Linear Effects of Mobility on COVID-19

	Dependent Variable:	
	Weekly % Changes in COVID-19 Cases	Weekly % Changes in COVID-19 Deaths
Coefficient in front of	0.944***	0.406***
Lagged Mobility	(0.0184)	(0.0201)
Day Fixed Effects	YES	YES
County Fixed Effects	YES	YES
Sample Size	354789	303976
R-sq	0.657	0.316
adj. R-sq	0.655	0.311

Notes: +, *, ** and *** represent significance at the 10%, 5%, 1% and 0.1% levels, respectively. Standard errors are given in parentheses.

Table 2 - Nonlinearities through Population Demographics

	Dependent Variable:					
	Weekly % Changes in COVID-19 Cases			Weekly % Changes in COVID-19 Deaths		
	Coefficient of Mobility for Counties:			Coefficient of Mobility for Counties:		
Threshold Variable:	Below Median	Above Median	Difference	Below Median	Above Median	Difference
Total Population	0.421***	0.957***	0.586***	-0.282**	0.416***	0.695***
	(0.0694)	(0.0185)	(0.0673)	(0.101)	(0.0202)	(0.0998)
Average Family Size	0.926***	0.961***	0.0363**	0.398***	0.410***	0.0122
	(0.0202)	(0.0191)	(0.0131)	(0.0220)	(0.0208)	(0.0142)
Median Age (Years)	0.923***	1.012***	0.0899***	0.401***	0.416***	0.0148
	(0.0188)	(0.0210)	(0.0138)	(0.0206)	(0.0226)	(0.0148)
65 Years and Over (%)	0.944***	0.983***	0.0389**	0.407***	0.385***	-0.0221
	(0.0185)	(0.0229)	(0.0149)	(0.0202)	(0.0250)	(0.0163)
Grandparents Responsible	0.953***	0.858***	-0.0939***	0.407***	0.366***	-0.0416*
for Grandchildrend (%)	(0.0185)	(0.0232)	(0.0148)	(0.0201)	(0.0254)	(0.0162)

Notes: +, *, ** and *** represent significance at the 10%, 5%, 1% and 0.1% levels, respectively. Standard errors are given in parentheses. Each pair of coefficients representing those for counties below and above median (of the threshold variable) are obtained from individual regressions. Difference is defined as above minus below median. All regressions include day fixed effects and county fixed effects. The sample sizes range between 303,858 and 354,644 across regressions. R-squared values range between 0.316 and 0.657 across regressions, whereas adjusted R-squared values range between 0.311 and 0.655 across regressions.

Table 3 - Nonlinearities through Economic Variables

	Dependent Variable:					
	Weekly % Changes in COVID-19 Cases			Weekly % Changes in COVID-19 Deaths		
	Coefficient of Mobility for Counties:			Coefficient of Mobility for Counties:		
Threshold Variable:	Below Median	Above Median	Difference	Below Median	Above Median	Difference
Per Capita Income	0.745***	0.948***	0.206***	0.335***	0.404***	0.0690***
	(0.0241)	(0.0184)	(0.0155)	(0.0265)	(0.0201)	(0.0169)
Median Household Income	0.975***	0.947***	-0.0255+	0.452***	0.404***	-0.0483**
	(0.0235)	(0.0185)	(0.0151)	(0.0256)	(0.0201)	(0.0165)
Poverty (%)	0.939***	1.026***	0.0877***	0.410***	0.362***	-0.0481**
	(0.0185)	(0.0222)	(0.0139)	(0.0202)	(0.0241)	(0.0148)
Health Insurance (%)	1.022***	0.938***	-0.0816***	0.385***	0.407***	0.0227
	(0.0221)	(0.0185)	(0.0137)	(0.0242)	(0.0202)	(0.0146)
Commuting Time	0.830***	1.015***	0.187***	0.336***	0.441***	0.105***
	(0.0202)	(0.0190)	(0.0129)	(0.0221)	(0.0207)	(0.0138)

Notes: +, *, ** and *** represent significance at the 10%, 5%, 1% and 0.1% levels, respectively. Standard errors are given in parentheses. Each pair of coefficients representing those for counties below and above median (of the threshold variable) are obtained from individual regressions. Difference is defined as above minus below median. All regressions include day fixed effects and county fixed effects. The sample sizes range between 303,858 and 354,644 across regressions. R-squared values range between 0.316 and 0.657 across regressions, whereas adjusted R-squared values range between 0.311 and 0.655 across regressions.

Table 4 - Nonlinearities through Occupations

	Dependent Variable:					
	Weekly % Changes in COVID-19 Cases			Weekly % Changes in COVID-19 Deaths		
	Coefficient of Mobility for Counties:			Coefficient of Mobility for Counties:		
Threshold Variable:	Below Median	Above Median	Difference	Below Median	Above Median	Difference
Management, Business, Science, and Arts (%)	0.656***	0.999***	0.346***	0.272***	0.431***	0.159***
	(0.0222)	(0.0186)	(0.0145)	(0.0240)	(0.0203)	(0.0157)
Service (%)	0.908***	1.034***	0.128***	0.398***	0.422***	0.0246+
	(0.0189)	(0.0205)	(0.0129)	(0.0206)	(0.0223)	(0.0138)
Sales and Office (%)	0.709***	1.083***	0.376***	0.433***	0.390***	-0.0429**
	(0.0204)	(0.0191)	(0.0138)	(0.0223)	(0.0208)	(0.0149)
Natural Resources, Construction and Maintenance (%)	0.966***	0.735***	-0.230***	0.411***	0.343***	-0.0679***
	(0.0185)	(0.0238)	(0.0163)	(0.0202)	(0.0261)	(0.0182)
Production, Transportation, and Material Moving (%)	1.029***	0.663***	-0.366***	0.434***	0.310***	-0.124***
	(0.0187)	(0.0213)	(0.0138)	(0.0204)	(0.0231)	(0.0149)

Notes: +, *, ** and *** represent significance at the 10%, 5%, 1% and 0.1% levels, respectively. Standard errors are given in parentheses. Each pair of coefficients representing those for counties below and above median (of the threshold variable) are obtained from individual regressions. Difference is defined as above minus below median. All regressions include day fixed effects and county fixed effects. The sample sizes range between 303,858 and 354,644 across regressions. R-squared values range between 0.316 and 0.657 across regressions, whereas adjusted R-squared values range between 0.311 and 0.655 across regressions.

Table 5 - Nonlinearities through Employment in Industries

	Dependent Variable:					
	Weekly % Changes in COVID-19 Cases			Weekly % Changes in COVID-19 Deaths		
	Coefficient of Mobility for Counties:			Coefficient of Mobility for Counties:		
Threshold Variable:	Below Median	Above Median	Difference	Below Median	Above Median	Difference
Agriculture, Forestry, Fishing and Hunting, and Mining (%)	0.954***	0.701***	-0.253***	0.405***	0.439***	0.0344+
	(0.0185)	(0.0253)	(0.0177)	(0.0201)	(0.0282)	(0.0203)
Construction (%)	0.970***	0.881***	-0.0880***	0.410***	0.390***	-0.0202
	(0.0188)	(0.0211)	(0.0136)	(0.0204)	(0.0231)	(0.0146)
Manufacturing (%)	1.095***	0.721***	-0.373***	0.485***	0.284***	-0.201***
	(0.0191)	(0.0201)	(0.0131)	(0.0209)	(0.0218)	(0.0139)
Wholesale Trade (%)	0.885***	0.989***	0.105***	0.401***	0.408***	0.00700
	(0.0200)	(0.0191)	(0.0129)	(0.0218)	(0.0208)	(0.0138)
Retail Trade (%)	0.918***	1.017***	0.0994***	0.436***	0.336***	-0.100***
	(0.0189)	(0.0206)	(0.0130)	(0.0206)	(0.0223)	(0.0138)
Transportation and Warehousing, and Utilities (%)	0.879***	1.107***	0.228***	0.381***	0.462***	0.0811***
	(0.0189)	(0.0206)	(0.0131)	(0.0206)	(0.0223)	(0.0140)
Information (%)	0.684***	1.034***	0.352***	0.260***	0.451***	0.190***
	(0.0211)	(0.0187)	(0.0136)	(0.0231)	(0.0204)	(0.0148)
Finance and Insurance, and Real Estate and Rental and Leasing (%)	0.677***	1.021***	0.347***	0.251***	0.446***	0.194***
	(0.0216)	(0.0187)	(0.0142)	(0.0236)	(0.0204)	(0.0155)
Professional, Scientific, and Management, and Administrative and Waste Management (%)	0.545***	0.997***	0.454***	0.368***	0.410***	0.0423*
	(0.0236)	(0.0185)	(0.0164)	(0.0260)	(0.0202)	(0.0183)
Educational Services, and Health Care and Social Assistance (%)	0.844***	1.046***	0.203***	0.360***	0.448***	0.0881***
	(0.0196)	(0.0195)	(0.0128)	(0.0213)	(0.0212)	(0.0136)
Arts, Entertainment, and Recreation, and Accommodation and Food Services (%)	0.762***	1.049***	0.289***	0.426***	0.393***	-0.0331*
	(0.0205)	(0.0191)	(0.0137)	(0.0222)	(0.0208)	(0.0147)
Other Services, except Public Administration (%)	0.886***	1.040***	0.155***	0.341***	0.500***	0.159***
	(0.0192)	(0.0200)	(0.0128)	(0.0209)	(0.0217)	(0.0137)
Public Administration (%)	0.943***	0.965***	0.0231+	0.426***	0.320***	-0.106***
	(0.0187)	(0.0212)	(0.0134)	(0.0203)	(0.0232)	(0.0144)

Notes: +, *, ** and *** represent significance at the 10%, 5%, 1% and 0.1% levels, respectively. Standard errors are given in parentheses. Each pair of coefficients representing those for counties below and above median (of the threshold variable) are obtained from individual regressions. Difference is defined as above minus below median. All regressions include day fixed effects and county fixed effects. The sample sizes range between 303,858 and 354,644 across regressions. R-squared values range between 0.316 and 0.657 across regressions, whereas adjusted R-squared values range between 0.311 and 0.655 across regressions.

Table 6 - Nonlinearities through School Attendance

	Dependent Variable:					
	Weekly % Changes in COVID-19 Cases			Weekly % Changes in COVID-19 Deaths		
	Coefficient of Mobility for Counties:			Coefficient of Mobility for Counties:		
Threshold Variable:	Below Median	Above Median	Difference	Below Median	Above Median	Difference
Nursery School, Preschool (%)	0.888***	0.981***	0.0945***	0.232***	0.490***	0.258***
	(0.0202)	(0.0190)	(0.0129)	(0.0221)	(0.0206)	(0.0137)
Kindergarten (%)	0.997***	0.802***	-0.194***	0.429***	0.332***	-0.0969***
	(0.0188)	(0.0211)	(0.0136)	(0.0204)	(0.0230)	(0.0146)
Elementary School (%) (Grades 1-8)	0.981***	0.697***	-0.284***	0.414***	0.329***	-0.0851***
	(0.0185)	(0.0227)	(0.0150)	(0.0202)	(0.0250)	(0.0165)
High School (%) (Grades 9-12)	0.994***	0.800***	-0.194***	0.425***	0.338***	-0.0872***
	(0.0187)	(0.0213)	(0.0140)	(0.0204)	(0.0233)	(0.0151)
College or Graduate School (%)	0.663***	0.992***	0.331***	0.328***	0.417***	0.0882***
	(0.0230)	(0.0186)	(0.0158)	(0.0253)	(0.0203)	(0.0176)

Notes: +, *, ** and *** represent significance at the 10%, 5%, 1% and 0.1% levels, respectively. Standard errors are given in parentheses. Each pair of coefficients representing those for counties below and above median (of the threshold variable) are obtained from individual regressions. Difference is defined as above minus below median. All regressions include day fixed effects and county fixed effects. The sample sizes range between 303,858 and 354,644 across regressions. R-squared values range between 0.316 and 0.657 across regressions, whereas adjusted R-squared values range between 0.311 and 0.655 across regressions.

Table 7 - Nonlinearities through Educational Attainment

	Dependent Variable:					
	Weekly % Changes in COVID-19 Cases			Weekly % Changes in COVID-19 Deaths		
	Coefficient of Mobility for Counties:			Coefficient of Mobility for Counties:		
Threshold Variable:	Below Median	Above Median	Difference	Below Median	Above Median	Difference
Less than 9th Grade (%)	1.028***	0.716***	-0.312***	0.402***	0.414***	0.0124
	(0.0188)	(0.0210)	(0.0135)	(0.0205)	(0.0226)	(0.0143)
9th to 12th Grade, No Diploma (%)	0.957***	0.772***	-0.185***	0.414***	0.233***	-0.181***
	(0.0185)	(0.0231)	(0.0146)	(0.0201)	(0.0250)	(0.0156)
High School Graduate (%) (Includes Equivalency)	0.950***	0.936***	-0.0137	0.419***	0.346***	-0.0723***
	(0.0186)	(0.0222)	(0.0150)	(0.0203)	(0.0241)	(0.0162)
Some College, No Degree (%)	0.964***	0.901***	-0.0626***	0.423***	0.350***	-0.0727***
	(0.0188)	(0.0208)	(0.0130)	(0.0204)	(0.0227)	(0.0139)
Associate's Degree (%)	1.005***	0.887***	-0.118***	0.487***	0.313***	-0.174***
	(0.0195)	(0.0196)	(0.0129)	(0.0211)	(0.0214)	(0.0137)
Bachelor's Degree (%)	0.721***	0.965***	0.247***	0.249***	0.418***	0.169***
	(0.0234)	(0.0185)	(0.0155)	(0.0255)	(0.0202)	(0.0170)
Graduate or Professional Degree (%)	0.669***	0.967***	0.302***	0.269***	0.415***	0.145***
	(0.0240)	(0.0185)	(0.0165)	(0.0263)	(0.0202)	(0.0181)

Notes: +, *, ** and *** represent significance at the 10%, 5%, 1% and 0.1% levels, respectively. Standard errors are given in parentheses. Each pair of coefficients representing those for counties below and above median (of the threshold variable) are obtained from individual regressions. Difference is defined as above minus below median. All regressions include day fixed effects and county fixed effects. The sample sizes range between 303,858 and 354,644 across regressions. R-squared values range between 0.316 and 0.657 across regressions, whereas adjusted R-squared values range between 0.311 and 0.655 across regressions.

Table 8 - Nonlinearities through Race

	Dependent Variable:					
	Weekly % Changes in COVID-19 Cases			Weekly % Changes in COVID-19 Deaths		
	Coefficient of Mobility for Counties:			Coefficient of Mobility for Counties:		
Threshold Variable:	Below Median	Above Median	Difference	Below Median	Above Median	Difference
Hispanic or Latino (%)	1.094***	0.878***	-0.214***	0.449***	0.385***	-0.0637***
	(0.0207)	(0.0190)	(0.0138)	(0.0225)	(0.0207)	(0.0149)
White (%)	0.948***	0.948***	0.000620	0.385***	0.432***	0.0468**
	(0.0193)	(0.0200)	(0.0132)	(0.0211)	(0.0217)	(0.0144)
Black or African American (%)	0.902***	0.975***	0.0751***	0.431***	0.390***	-0.0411**
	(0.0203)	(0.0191)	(0.0133)	(0.0221)	(0.0209)	(0.0146)
American Indian and Alaska Native (%)	0.948***	0.943***	-0.00466	0.403***	0.427***	0.0236
	(0.0185)	(0.0224)	(0.0142)	(0.0202)	(0.0245)	(0.0155)
Asian (%)	0.841***	0.959***	0.121***	0.421***	0.404***	-0.0179
	(0.0241)	(0.0185)	(0.0171)	(0.0266)	(0.0202)	(0.0192)

Notes: +, *, ** and *** represent significance at the 10%, 5%, 1% and 0.1% levels, respectively. Standard errors are given in parentheses. Each pair of coefficients representing those for counties below and above median (of the threshold variable) are obtained from individual regressions. Difference is defined as above minus below median. All regressions include day fixed effects and county fixed effects. The sample sizes range between 303,858 and 354,644 across regressions. R-squared values range between 0.316 and 0.657 across regressions, whereas adjusted R-squared values range between 0.311 and 0.655 across regressions.

Table A.1 - Descriptive Statistics

	Variable:		
	COVID-19 Cases	COVID-19 Deaths	Mobility
Average	6.240	3.127	-8.48%
Standard Deviation	1.896	1.330	6.15%
Median	6.613	3.273	-7.37%
5th Percentile	2.734	0.779	-20.40%
25th Percentile	4.997	2.224	-11.70%
75th Percentile	7.745	4.130	-4.41%
95th Percentile	8.652	5.063	0.38%
Number of Observations	814,138	580,611	399,108
Correlation with:			
COVID-19 Cases	1.000		
COVID-19 Deaths	0.813	1.000	
Mobility	0.401	0.272	1.000

Notes: COVID-19 cases and deaths are represented as per 100,000 people, seven day moving average. Mobility is measured as the time spent outside of residential locations relative to the period between January 3 and February 6, 2020.