Introduction

Following the discovery and rapid spread of coronavirus disease 2019 (COVID-19), governments around the world have implemented social distancing measures to prevent people from leaving their homes and to limit human interaction. In the United States, the federal government released the 15 Days to Slow the Spread program, a set of public health guidelines that was developed by the CDC and includes recommendations to physically distance and stay at home whenever possible. Although this initiative coincided with a dramatic rise in social distancing across the country, few studies have examined about how increases in social distancing varied across social and demographic groups during this time.[1]

One sign that group-level differences in social distancing had emerged following the COVID-19 outbreak is the evidence of demographic and social disparities in COVID-19 prevalence rates (Hooper, Nápoles, and Pérez-Stable 2020; Koh 2020). Although these disparities are partly a result of comorbidity patterns, they also point to differences in how people have altered their movement through society in response to this disease (Courtemanche et al. 2020). Differences in social distancing levels may be especially pronounced in the United States, where high levels of economic inequality contribute to disparities in employment arrangements and economic resources that allow for social distancing. For instance, lower-income workers are less likely to hold jobs that provide paid sick leave, and workers without sick leave are less likely to remain home from work when they are sick (Derigne, Stoddard-Dare, and Quinn 2016). Moreover, many jobs held by lower-income workers consist of tasks that must be carried out in person and in close proximity to others, while higher-paying jobs can often be performed remotely (Dingel and Neiman 2020). As a result, the widespread transition to working from

[1] An important exception is a paper by Weill and coauthors (2020), which found a strong connection between income and social distancing levels in a county-level analysis of data tracking people's daily movements.

home that started in March 2020 may have been a white collar phenomenon.[2] Finally, low-income households are less likely to have savings, second homes, and other economic resources that facilitate changing one's daily routine in response to new events. One sign of the relative ease with which the rich have socially distanced is the large number of residents from higher-income neighborhoods who out-migrated from Manhattan at the outset of the COVID-19 crisis in New York City (Quealy 2020).

These considerations suggest that occupational status and income were particularly important dimensions along which people's levels of social distancing varied following the outbreak of COVID-19. In this study, I examine how these factors influenced people's everyday movements during this period. Using a dataset that tracks people's physical movements through their mobile phone activity, I estimate several models evaluating the effects of income and occupational status on stay-at-home patterns. I find a large and positive effect of neighborhood-level median income on social distancing, including diminished levels of leaving the home to go to work. I also estimate models that include a set of occupational measures based on job categories from The Bureau of Labor Statistics. According to these models, the lowest paying occupations were associated with smaller increases in social distancing, while the highest paying jobs experienced the largest jumps in social distancing. This finding is particularly striking given that unemployment in the early stages of the COVID-19 pandemic increased more among people in lower paying occupations (BLS 2020). These results suggest that the relative prevalence of COVID-19 among lower-income households may be attributable in part to an occupational

[2] The paucity of lower-paying jobs that can be performed remotely also has implications for the relationship between occupation and COVID-19 prevalence, especially for companies that prioritize assuaging customers' fears above protecting their employees. This is suggested by a recent spike in OSHA lawsuits, in which many companies – including Target, Amazon, McDonald's, REI, Cargill, Smithfield Foods, Delta Airlines, Urban Outfitters, and General Electric – have been accused of pressuring employees that have been diagnosed with COVID-19 to hide their diagnoses from their coworkers (Eidelson 2020).

structure that has failed to accommodate lower-income workers. In the absence of employment arrangements enabling working from home or subsidizing reduced levels of work, lower-income workers face a choice between risking exposure to COVID-19 or losing employment. I conclude with a discussion of the policy implications of these economically patterned gaps in social distancing levels.

Methods

Data and Measures

The data for this study come from SafeGraph, a company that tracks foot-traffic patterns from over 45 million mobile devices in the United States. This data is based on an opt-in panel of mobile users whose devices are pinged throughout the day. To protect the anonymity of these users, Safegraph aggregates this data to census block groups (CBG), which are subdivisions of census tracts that contain about 1,400 people on average (U.S. Census 2019). The social distancing patterns analyzed in this study are based on a sample of 212,099 CBGs.

I used two measures to capture changes in social distancing levels. The first, median daily time at home, tracks the amount of time spent at home among devices whose homes fall within the boundaries of a CBG. Mobile devices are assigned to a home if they have been geolocated to a common nighttime location (within a 153 square-meter rectangle) over a six-week period. The second measure follows the proportion of devices exhibiting full-time work behavior. This measure is based on the number of devices that were away from home for a period longer than six hours between 8am and 6pm. Averaging across these daily measures, I computed social distancing levels for two time periods: the two weeks preceding March 16 (the start of the 15 Days to Slow the Spread initiative), and the three weeks following March 16. To focus on

changes in workweek social movement patterns, I chose to exclude weekend social distancing levels from these averages.[3]

The explanatory and control variables in these models come from the 2014-2018 five-year pooled American Community Survey (ACS). To account for demographic differences among CBGs, I controlled for proportions of male, Black, Asian, and non-white Hispanic residents. I also included several economic measures, including median income, the proportion of residents over 25 with a college degree, the poverty rate, and the unemployment rate. Finally, I added measures for occupational groups (5 categories) and occupational subgroups (25 categories).[4]

Analytical Strategy

The effect of median income on social distancing was estimated with several spatial error models (Ward and Gleditsch 2019). The spatial error model is a kind of mixed model that uses a random effect to account for the dependency structure of the residuals associated with spatially clustered observations. The model has the following structure:

$$y_i = \boldsymbol{x}_i\beta + \varepsilon_i + \lambda \boldsymbol{w}_i\xi_i$$

$$\varepsilon \sim N(0, \sigma^2 I)$$

Where the error term consists of a spatial component $\lambda \boldsymbol{w}_i\xi_i$ and a spatially uncorrelated component ε_i. In this equation, λ denotes the level of spatial correlation among the residuals. Given that CBGs often resemble neighboring CBGs, this will likely be positive in the models

[3] The exclusion of weekend social distancing data does not change the substantive interpretation of the results presented in this paper.

[4] Occupational subgroup controls are based on the 23 major occupational groups from the 2018 Standard Occupational Classification (SOC) system (U.S. Census Bureau 2018). Two of these groups, Healthcare Practitioners and Technical Occupations and Protective Service Occupations, have been further disaggregated to create the 25 occupational subgroups used in this study. The 5 occupational group controls are based on the 6 high-level aggregation titles from the SOC system. One of the 6 high-level titles, Military Specific Occupations, was excluded from the present study.

estimated in this paper. A likelihood ratio test giving a low probability that $\lambda = 0$ indicates the necessity of using a model that accounts for spatial clustering. $\boldsymbol{w}_i$ indexes the CBGs that neighbor CBG i. Neighboring CBGs are determined using Queen's criterion, which groups regions based on whether they share a border or a vertex (Anselin 2020).

Maximum likelihood estimates of the model parameters were computed using the spdep package in R (Bivand 2020). The results are organized into three sets of models. The first two sets consist of CBG-level estimates of the effect of median income on time at home and full-time work behavior (spending at least six hours of the day in a single location outside the home) for each of the 100 most populous metropolitan statistical areas (MSAs) in the U.S. For the third set of models, I aggregated the CBG data to the county level and estimated the effect of median income on full-time work behavior for the entire U.S. This third set of models introduces several occupation and occupation group variables. I include these measures to evaluate whether the effect of income on social distancing can be attributed to differences in the jobs held by lower and higher-income mobile device users.

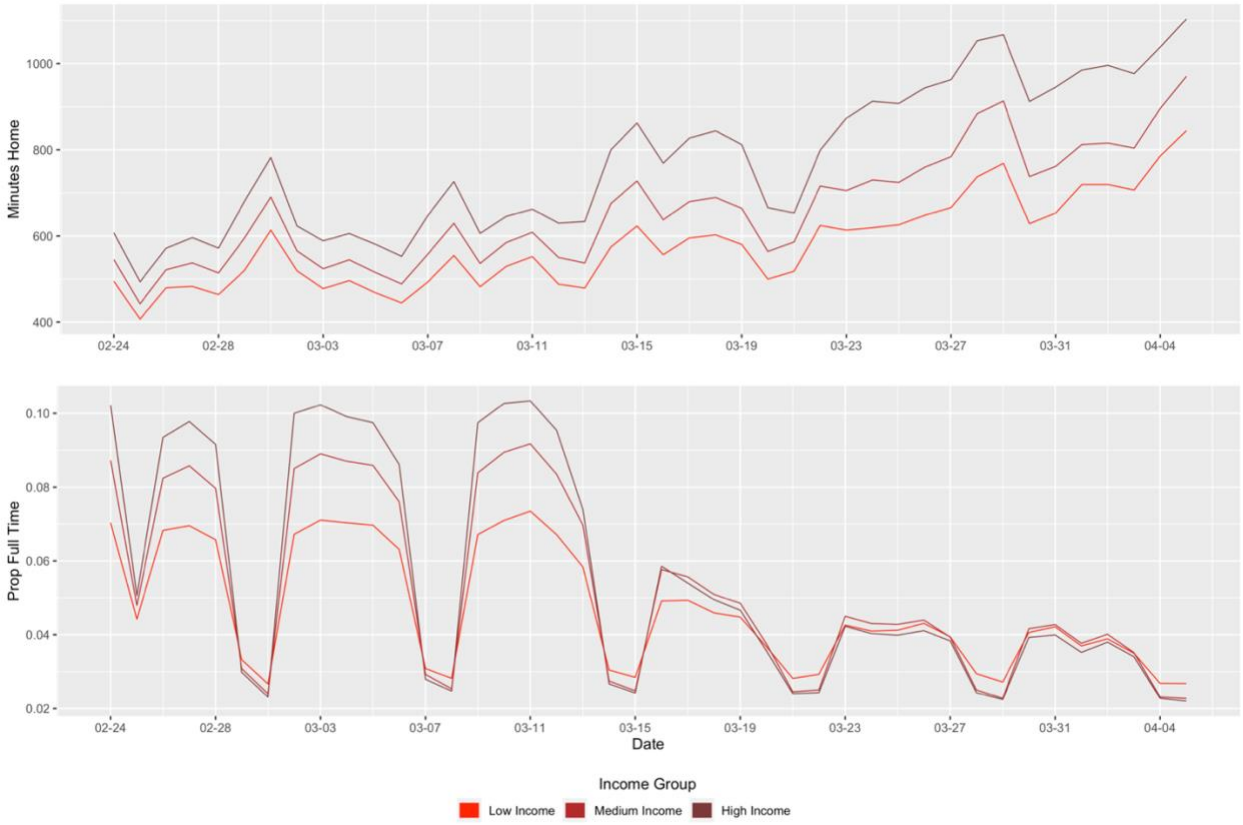
Results

Trends in Time at Home and Full-Time Employment

Figure 1 shows trends in social distancing by income groups, which are divided by lower, middle, and upper income tertiles. Looking first at the plot at the top of the figure, daily minutes spent at home increased for all three groups during the month of March 2020. However, time at home increased more in higher-income CBGs: the gap between the income groups grew as the days passed. The bottom plot displays changes in rates of full-time work behavior, proxied by the proportion of residents that were away from home for at least six hours of the day. Before March 16th, a greater proportion of devices in higher-income CBGs engaged in full-time work

behavior. After the 15 Days to Slow the Spread initiative began, rates of full-time work behavior in higher-income and middle-income CBGs dropped sharply. Full-time work rates from this point onward were comparable across the income groups.

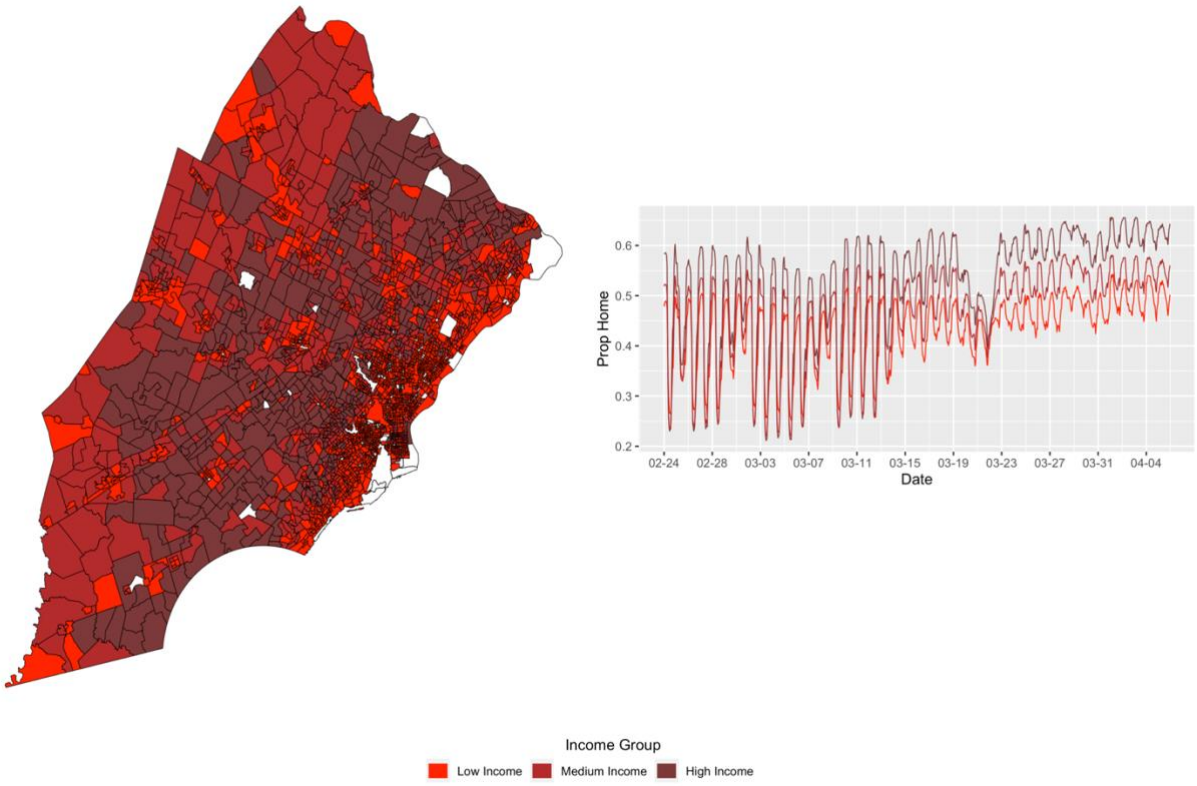
Figure 1. Trends in Daily Time Home and Full Time Employment by Income



To provide a more detailed picture of how changes in social distancing varied over the course of the day, Figure 2 focuses on changes in hourly stay-at-home patterns in the Philadelphia MSA. The map on the left shows the geographic distribution of lower, middle, and upper income CBGs across the region. This map shows a moderate amount of segregation by income: many lower-income CBGs can be found on the eastern part of the map (closer to downtown), while higher-income CBGs are in the central and western areas of the map (the suburbs). This pattern is representative of many large MSAs, suggesting that income differences

in social distancing may produce social distancing disparities at larger geographic levels, such as census designated places. The plot on the right shows *hourly* fluctuations in at-home rates. For every 24-hour period, the trend lines peak in the middle of the night and reach their lowest points in the early afternoon. Before social distancing measures were enacted, a lower proportion of residents of high-income CBGs were at home in the middle of the day. This changed in the middle of the month: daytime stay-at-home rates for high-income CBGs went from the lowest to the highest of the three income groups. Notably, income differences in nighttime stay-at-home rates, the peaks in the plot, experienced little change. Low-income CBGs had lower nighttime stay-at-home rates over the entire study period. This suggests the broadening gap in social distancing between high and low-income CBGs reflected in Figure 1 can be attributed to changes in daytime behaviors.

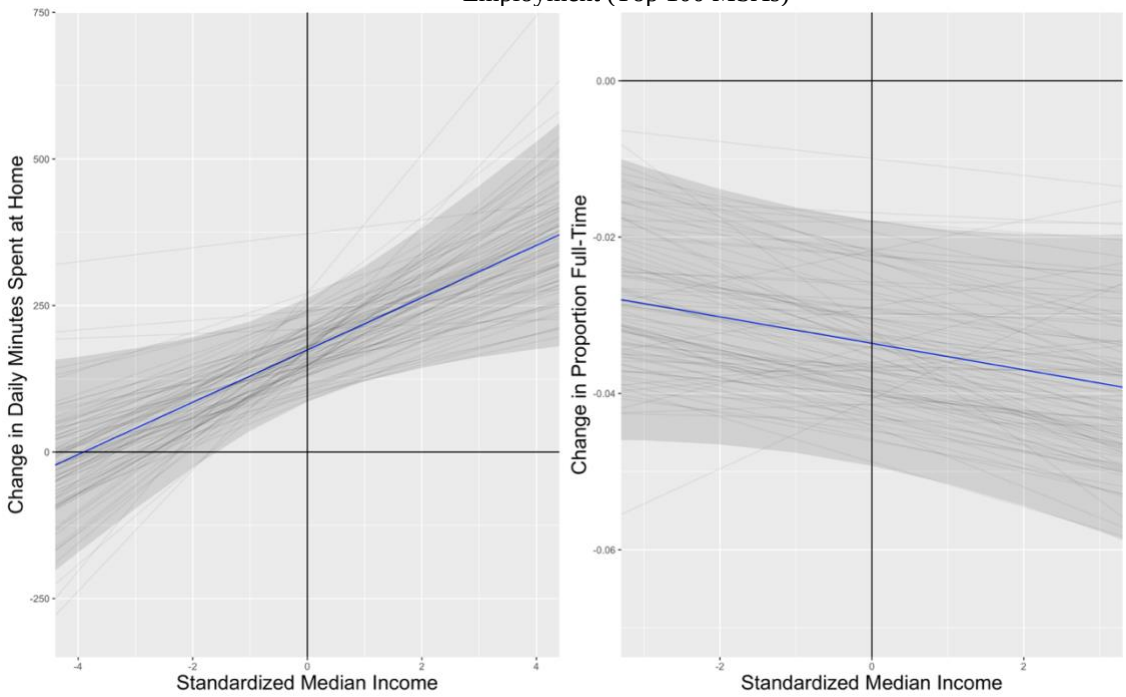
Figure 2. Relationship Between Income and Hourly at Home Rate in Philadelphia



Models of Time at Home and Full-Time Employment

Figure 3 shows regression lines for the effects of income on changes in time at home and full-time employment. Spatial error models were estimated for 100 MSAs, each of which is represented by a grey regression line. The mean predicted value of the outcome across these MSAs is indicated by the blue line, and the two standard-deviation spread of predicted values is represented by the grey shaded region. Looking first at the plot on the left, the positive y-intercepts of the grey regression lines indicate that time at home increased for all 100 MSAs. The positive slopes of these lines show that higher-income CBGs experienced larger increases in time at home for every MSA in the sample. The slope of the blue regression line is 44.23, meaning that the average effect of a one standard-deviation increase in median income across the 100 MSAs is a roughly forty-four minute increase in the median time spent at home.[5]

Figure 3. Effect of Median Income on Change in Daily Minutes Spent at Home and Change in Proportion Full-Time Employment (Top 100 MSAs)



[5] This statistic represents the unweighted average effect of income across the MSAs. Weighting by MSA population or number of CBGs does not change the substantive interpretation of the results.

The blue regression line in the plot at the right of the figure further supports a general pattern in which higher-income CBGs experienced larger increases in social distancing during the study period. For most, but not all, MSAs in the sample, higher median income levels were associated with greater declines in full-time employment behavior. That some MSAs show a positive association between income and full-time work behavior may reflect occupational differences among MSAs. In cities with higher employment in the service sector, for instance, layoffs may have countered the effect of transitioning to working from home, resulting in a neutral or even positive relationship between median income and change in full-time employment behavior. Still, the slope of the blue line is negative, indicating an average negative association between neighborhood income and full-time employment behavior across the sample of 100 MSAs.

While the Figures 1-3 show that neighborhood-level income differences explain varying levels of social distancing following the COVID-19 outbreak, this relationship may be driven by occupational differences between high and low-income neighborhoods. Table 1 shows the results of county-level models testing this possibility. Models 1 and 2 include the variables from the previous models, while models 3 and 4 introduce the occupation measures. Specifically, model 3 includes five measures of occupational groups – managerial occupations; service occupations; sales and office occupations; natural resources, construction, and maintenance occupations; and production, transportation, and material moving occupations. Model 4 leaves out the occupational group measures and instead includes measures of the twenty-five occupations within these groups.

Table 1: Spatial Autocorrelation Models of Change in Proportion Employed Full-Time

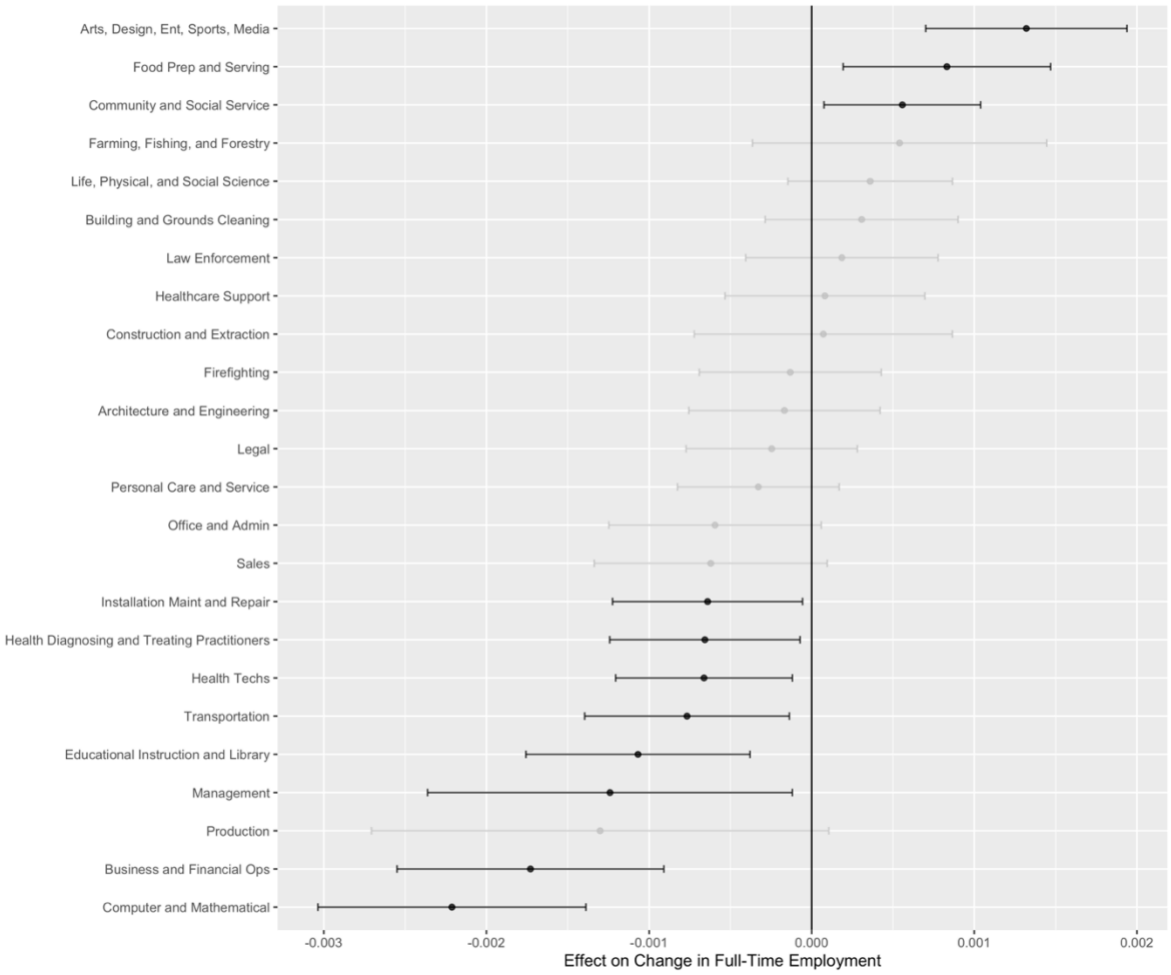
	Dependent variable:			
	Change in Proportion Employed Full-Time			
	(1)	(2)	(3)	(4)
Percent Male	0.0005^{**}	0.001^{***}	0.001^{**}	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Percent Black	0.002^{***}	0.001^{**}	0.001^{***}	0.001^{**}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Percent Asian	0.001^{***}	0.002^{***}	0.002^{***}	0.002^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Percent Non-white Hispanic	0.0002	0.0005	0.0005	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Percent College Degree	-0.002^{***}	-0.00002	0.0002	0.0002
	(0.0003)	(0.0004)	(0.0004)	(0.001)
Poverty Rate	0.004^{***}	-0.0001	-0.0001	-0.0002
	(0.0004)	(0.001)	(0.001)	(0.001)
Unemployment Rate	0.0001	0.0005	0.0005	0.001^{*}
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Median Income		-0.006^{***}	-0.006^{***}	-0.004^{***}
		(0.001)	(0.001)	(0.001)
Constant	-0.030^{***}	-0.030^{***}	-0.031^{***}	-0.032^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Occupation Group Controls	No	No	Yes	No
Occupation Controls	No	No	No	Yes
λ	0.123	0.121	0.121	0.115
Observations	3,218	3,218	3,218	3,217
σ^2	0.0002	0.0001	0.0001	0.0001
Akaike Inf. Crit.	$-18{,}778.560$	$-18{,}898.290$	$-18{,}905.490$	$-19{,}043.020$

*p<0.1; **p<0.05; ***p<0.01

According to the models' Akaike Information Criterion (AIC) scores, each model fits the data better than the previous model. Particularly large drops in the AIC resulted from adding median income to the model (Model 2) and incorporating the occupation measures (Model 4). Conversely, the occupational group measures, which provide less detail than the occupation measures, did little to improve model fit. Comparing models 2 and 4, the inclusion of occupation attenuated the coefficient on median income by 50%, from -.006 to -.004. Still, the effect of income was larger than any of the other coefficients in the final model.

Figure 4 looks at the coefficients estimated for each occupation in Model 4. Positive coefficients on the occupation measures indicate occupations associated with less social distancing (smaller decreases in full-time work behavior). The three occupations with positive and significant coefficients are Arts, Design, Sports, and Media; Food Preparation and Serving; and Community and Social Service. According to the Bureau of Labor Statistics, the mean salaries for these occupations were $61,960, $26,670, and $50,480 in 2019 (BLS 2020). The three occupations with the largest significant and negative coefficients – the jobs associated with the largest drops in full-time employment behavior – are Computer and Mathematical; Business and Financial Operations; and Management. These occupations had annual wages of $93,760, $78,130, and $122,480, respectively, in 2019. These numbers suggest that neighborhoods with greater employment in higher paying occupations experienced larger declines in full-time employment behavior, despite the fact that fewer people holding these jobs were laid off during the study period.

Figure 4. Effects of County-level Occupation Proportions on Change in Full-Time Employment



Discussion

The beginning of the COVID-19 outbreak in the United States marked the enactment of a public health campaign to limit the spread of the disease through social distancing. As this study shows, trajectories of social distancing during this time varied widely depending on neighborhood income levels. Increases in time at home were larger among residents of higher-income neighborhoods, while transitioning to working from home was more common among these residents as well. Furthermore, the relationship between income and working from home is partly a consequence of occupational differences among the residents of high and low-income neighborhoods. Neighborhoods with higher proportions of certain high-paying jobs experienced the largest drops in working outside the home, while neighborhoods with higher rates of the lowest paying jobs witnessed the smallest drops in working outside the home.

The effects of the occupation measures on social distancing levels may reflect differences in the activities associated with high and low-paying jobs. While many lower paying jobs – those in Food Preparation and Serving, for instance – consist of tasks that need to be performed on-sight, many higher paying jobs can be completed remotely. As a result, transitioning to working from home has been more common among people with higher-paying positions. This arrangement has forced workers in low-paying positions to choose between risking exposure to COVID-19 and losing their jobs, while enabling employees in higher paying occupations to insulate themselves from the disease without losing employment. Further, many lower paying jobs do not include benefits such as paid sick leave and health insurance that are often provided to those in better paying positions. Without paid sick leave, workers are motivated to conceal concerns about having contracted COVID-19 from their employers. The absence of health insurance also deters workers who fear they have contracted COVID-19 from getting tested for

the disease. These factors create dangerous incentives for workers to ignore the signs that they might be sick and continue their usual everyday activities.

Encouragingly, this study suggests that social distancing levels in lower-income communities can be increased by policies directed toward the companies that employ lower-income workers. A mandate requiring that these companies provide paid sick leave to employees with a COVID-19 diagnosis, along with initiatives to facilitate access to free testing in these communities, would go a long way in redressing the institutional factors that contribute to the social distancing gaps that I have identified here. Alternatively, the government should consider subsidizing businesses that cannot operate remotely. The U.S. took a step in this direction in the early months of the pandemic, providing forgiveness on Payment Protection Program (PPP) loans to businesses that spent a portion of this money on their employees' salaries. A more aggressive action would to be provide money to small businesses (both employees and their employers) to close their doors temporarily. Particularly for non-essential businesses that cannot follow social distancing guidelines – restaurants, bars, gyms, and concert venues, for example – such temporary subsidies would preserve jobs and businesses while preventing the spread of COVID-19 through lower-income communities and the public at large.

The outbreak of COVID-19 in the U.S. has produced new forms of social inequality, many of which are perpetuated by an economy that distributes money and other resources unevenly through society. I have shown that social distancing is associated with higher levels of income and that this relationship is a function of the jobs held by people at different income levels. These findings contribute to a larger literature documenting the ways in which economic inequality produces negative public health consequences (Wilkinson and Pickett 2009**)**. Finally, I have put forth some policy ideas to promote social distancing in lower-income areas, but more

far-reaching reforms are needed to ensure that Americans have health insurance, employment benefits, savings, and other economic resources necessary to adopt new behaviors in the event of a future pandemic.

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