Understanding Socioeconomic Disparities in Travel Behavior during the COVID-19 Pandemic

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Abstract

We document the magnitudes of and mechanisms behind socioeconomic differences in travel behavior during the COVID-19 pandemic. We focus on King County, Washington, one of the first places in North America where COVID-19 was detected. We leverage novel and rich administrative and survey data on travel volumes, modes, and preferences for different demographic groups. Large average declines in travel and public transit use due to the pandemic and related policy responses mask substantial heterogeneity across socioeconomic groups. Travel declined considerably less among less-educated and lower-income individuals, even after accounting for mode substitution and variation across neighborhoods in the impacts of public transit service reductions. As policy has become less restrictive and travel has increased, the size of the socioeconomic gap in travel behavior has remained stable, and remote work capabilities have become increasingly important in explaining this gap. Our results imply that disparities in travel behavior across socioeconomic groups may become an enduring feature of the urban landscape.

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1 Introduction

The novel coronavirus (COVID-19) led to swift and unprecedented changes in people's travel behavior around the world. A combination of voluntary precautions and policy responses by governments, including city lockdowns and stay-at-home orders, sharply curtailed trips for both work and leisure in many places, potentially helping to contain the spread of the virus. Such orders have since been relaxed in many places. However, the ability of different groups of individuals to adjust their travel behavior in the face of the pandemic and various changing policy directives has raised important equity concerns.

In this paper, we study how and why changes in travel behavior in response to COVID-19 vary with socioeconomic status. We focus on King County in the U.S. state of Washington. King County is home to Seattle, one of the first cities in North America affected by the pandemic and one with some of the earliest and most sweeping policy responses. Using anonymized geolocated cell phone data from SafeGraph Inc., we first document that overall changes in travel in response to COVID-19, the initial lockdown, and the reopening period correlate with neighborhood disadvantage. Exploiting passenger boardings information derived from sensors on board King County Metro's fleet of vehicles, we explore changes in public transit use in particular and how those changes vary over time as well as with neighborhood demographics. Supplementary administrative data on transit boardings by individuals using full-fare transit cards versus reduced-fare cards available only to lower-income individuals allow us to focus on differential responses by higher- and lower-income riders, rather than neighborhoods. Finally, we explore the mechanisms behind the differential changes in travel behavior during the pandemic. We take advantage of both administrative data and the results of a novel survey of low-income individuals in King County to uncover the sources of the observed changes in mobility across socioeconomic groups both in early as well as later stages of the pandemic period.

We document a steep decline in mobility in King County as the pandemic took hold. Based on cell phone tracking data, the average number of census block groups (CBGs) people visited each day (excluding their home CBG) fell by 57% between February and April 2020. During the same period, public transit use declined by an even sharper 74%. While still well below pre-pandemic levels, overall mobility recovered slightly as the local economy began to reopen. Public transit recovered less and with a substantial lag relative to overall travel.

The large average declines in travel overall, and public transit use in particular, mask substantial heterogeneity across socioeconomic groups. Mobility responses were particularly swift, pronounced, and persistent among more highly educated and higher-income neighborhoods and individuals. We examine the underlying mechanisms behind these changes in travel behavior across socioeconomic groups. We focus specifically on the roles of transportation mode substitution, public transit service adjustments, and commuting for work.

First, residents of more-educated neighborhoods engaged in a greater degree of mode substitution, but only early on in the crisis. During the initial stages of King County's lockdown, we observe a differentially large decline in public transit use relative to overall travel in highly educated neighborhoods. This implies that high-income residents disproportionately shifted away from public transit and toward cars. However, the role of mode substitution in driving differences in travel behaviors across socioeconomic groups has faded over time, suggesting a convergence in substitution elasticities.

Second, public transit service adjustments in the aftermath of the lockdown can explain only a small fraction of the gap in transit use between higher- and lower-income riders. Similar to many other transit systems in North America, King County transit authorities limited service in various parts of the local public transportation system beginning in mid-March. To the extent that these service adjustments differentially affected residents of more- versus less-educated neighborhoods, it could help to explain the differential response in travel behavior we observe between groups. However, ridership of higher-income users relative to lower-income users declines as much or more within transit routes as between transit routes, indicating that the supply of public transit plays little role in driving differential changes in transit use across socioeconomic groups.

Finally, we find that the relative inability of less-educated and lower-income people to work remotely has been an important contributor to the smaller mobility response for that group, particularly as the local economy has begun to reopen. Characteristics correlated with remote work capabilities (occupation mix and internet, computer, and smartphone access) explain 30% of the gap in travel behavior between residents of more- and less-educated neighborhoods in July. These controls have greater explanatory power during the reopening period than in the depths of the lockdown. The disparity in the extent to which more- and less-educated individuals can perform their jobs at home therefore appears to be an important and growing contributor to the socioeconomic gap in travel behavior as the pandemic unfolds.

Additionally, in the depths of the lockdown, and even more so during the reopening period, weekly and daily cycles of travel consistent with commuting for work remain conspicuous among residents of less-educated neighborhoods and among individuals using reduced-fare public transit cards. For residents of more-educated neighborhoods and individuals using regular-fare public transit cards, commute cycles are clear in the data before the crisis but largely vanish after the pandemic took hold. Under the conservative assumption that weekday trips are for work and weekend trips are for other activities, these changes again point to an important and growing role of commuting for work as an explanation for socioeconomic differences in travel behavior in the pandemic's aftermath.

We complement these results using newly collected survey data from an ongoing study in King County. The survey highlights how intended and actual travel changed among low-income individuals as the COVID-19 crisis took hold. We find that low-income individuals consistently report intentions to use transit for activities that could be deemed essential, such as for work, school, and health, even as the crisis and its policy response materialized in March. As policies restricted movement more broadly and employment declined, actual reported essential travel fell sharply. Work-related travel only began recovering after the local economy started to reopen in late June. Consistent with our findings based on remote work proxies as well as weekly and daily cycles of travel, our survey results suggest that the ability to perform work at home has become increasingly important in generating socioeconomic disparities in travel behavior. As the the local economy reopens, higher-income individuals who are more likely to perform their jobs at home continue to do so while lower-income individuals who cannot begin commuting more regularly.

Our results add to the growing body of evidence suggesting that the burden of the pandemic, not only in terms of its direct health effects but also in terms of the economic costs of avoidance and mitigation efforts, are spread unevenly across demographic groups. Several recent papers have identified COVID-19's disparate effects along other dimensions. For example, Abedi et al. (2020) shows that the virus' incidence varies across demographic groups in the U.S. Borjas (2020) and Schmitt-Grohé et al. (2020) demonstrate that COVID-19 testing rates vary systematically by neighborhood demographics in New York City. Baker et al. (2020) document heterogeneity in household consumption patterns across demographic groups and by income level in response to the pandemic. Adams-Prassl et al. (2020), Cajner et al. (2020), Fairlie et al. (2020), Montenovo et al. (2020), and Kahn et al. (2020) highlight how the economic costs of the crisis have been borne disproportionately by lower-income groups, for whom working remotely is less likely to be feasible and for whom income and job losses overall have been greater in the aftermath of the crisis.

We contribute to this literature by illustrating the magnitude and sources of heterogeneity in the mobility impacts of the crisis. Brzezinski et al. (2020) and Couture et al. (2020) document differences in mobility by education across U.S. counties. We build on this work by combining several sources of administrative and survey data from one jurisdiction to show that these differences remain at the neighborhood and individual levels and to provide evidence on why these disparities emerge. Understanding COVID-19's heterogeneous mobility impacts is important because they could represent both causes and consequences of many of the other documented disparate effects of the pandemic. To the extent that less-educated and lower-income groups continue to travel at higher rates than more-educated and higher-income groups (especially in modes frequently necessitating interaction with other people, like public transit), it could contribute to higher viral transmission rates among those groups (McLaren 2020). The higher mobility among less-educated and lower-income groups is also potentially a consequence of their inability to work remotely and home conditions that are generally less hospitable to sheltering in place due to lack of adequate internet access, space constraints, and limited access to outdoor areas. Leveraging new insights on remote work (Dingel and Neiman 2020, Bick et al. 2020, Bartik et al. 2020), we find that the differential ability to perform work at home has been a key contributor to socioeconomic disparities in travel behavior. Moreover, the ability of remote work to explain socioeconomic differences in travel behavior appears to be greater outside of full lockdown situations, indicating that these differences may become more entrenched.

Our results have important policy implications. The relatively inelastic mobility response to COVID-19 among less-educated and lower-income groups can be traced at least in part to economic necessity, and in particular the need to travel to jobs that cannot be performed remotely. Our findings make clear that policymakers' decisions about which types of businesses may open and when during a pandemic will have profound implications for travel behavior across socioeconomic groups. Raising the opportunity cost of traveling for work via transfers tied to staying home (for example, through the unemployment insurance system) could reduce socioeconomic disparities in travel, and in turn also in disease exposure. However, such measures could come at the cost of forgoing certain, possibly critical, goods and services during the crisis, and might translate into even larger job losses among individuals at the lower end of the income distribution. Importantly, however, differences in the ability to perform jobs at home does not explain the entire the gap in travel behavior. As highlighted by Brzezinksi et al. (2020), this could reflect differential messaging or degrees of compliance with directives regarding non-essential travel.

Our findings also help to foreshadow possible changes in mobility patterns and modes as local economies reemerge from the crisis and individuals adapt to changes to the disease risk environment. The large and longer-lived drop in public transit use relative to overall mobility points to substitution away from modes that involve close proximity to others and toward those that do not (e.g., single-occupancy driving). To the extent that substitution away from transit persists, it could have important implications for traffic congestion, pollution, and the economic viability of transit systems. There also may be a lasting shift to remote working for some types of jobs (Bartik et al. 2020, Lavelle 2020, Molla 2020), which could generate more entrenched disparities in travel behaviors to the extent that people in different socioeconomic groups hold jobs that can be performed remotely at different rates.

2 Mobility Responses to the COVID-19 Pandemic

2.1 The King County Context

We focus on King County, Washington. King County was among the first North American locations impacted by the pandemic, and thus has one of the longest post-COVID-19 periods to analyze. The first confirmed COVID-19 case on U.S. soil was identified in the state of Washington on January 21, 2020, and one of the first COVID-19-related deaths in the U.S. occurred in the Seattle area on February 28. The outbreak of COVID-19 at the Life Care Center in Kirkland, a suburban area in King County just east of Seattle, in late February set the wheels in motion for sweeping state and local government policy responses. The Seattle mayor issued a proclamation of civil emergency on March 3. Public schools as well as restaurants, bars, and entertainment facilities statewide were closed March 16. The state issued its official stay-at-home order March 23, two days before all nonessential businesses in the state were forced to close. Approximately three months later, on June 19, King County began to allow certain nonessential activities to resume and permitted some business to reopen with restrictions as part of its Phase 2 of the COVID-19 response. However, Washington's governor paused the reopening process indefinitely at the end of July in an effort to slow the spread of COVID-19.

King County also provides data that uniquely speak to travel patterns in general and differences in travel behavior by income in particular. First, through a partnership with King County Metro, we have access to multiple sources of transit ridership information in King County. In particular, we have data on passenger counts derived from sensors on board most King County buses. We also have separate, individual-level boarding data based on "taps" by transit fare cards. Taps by regular-fare versus means-tested reduced-fare cards allow us to track trips by higher- and lower-income riders separately. This differs from data used in most papers on travel behavior during the pandemic, which typically infer income from residential location.

Second, we were in the midst of a randomized controlled trial studying transit fare policy when COVID-19 cases began to emerge in North America and when King County went into lockdown.[1] That study included surveys that provide detail on travel intentions and behavior during the shutdown and reopening period.

2.2 Changes in Overall Mobility

We use data from SafeGraph Inc. to measure overall changes in travel intensity as the COVID-19 crisis unfolded. SafeGraph tracks the locations of millions of mobile devices on which individuals have agreed to allow applications to access data on their precise locations. These data are anonymized and aggregated to CBGs. SafeGraph determines a device's home CBG based on where it resides most frequently. Using origin and destination information, the SafeGraph data allow us to construct high-frequency measures of mobility among individuals.[2]

In King County, we observe around 100,000 devices in the SafeGraph data, or about 78 devices per CBG.[3] Assuming each device is attached to one individual, this corresponds to a

[1]See Brough et al. (2020b) for results from a pilot phase of that study.

[2]No device-level demographic information is available in the SafeGraph data. More information about the SafeGraph data can be found at https://docs.safegraph.com/docs/social-distancing-metrics.

[3]There are 1,421 CBGs in King County with positive population. Descriptive statistics for these CBGs appear in Appendix Table A.1.

roughly 5% sample of all individuals living in King County. Coverage rates are not strongly correlated with socioeconomic characteristics of King County neighborhoods.[4] Our main measure of mobility derived from the SafeGraph data is the average number CBGs visited each day, other than the home CBG, per device. We focus primarily on the relationship between travel behavior and the share of adult residents in a CBG with a bachelor's degree because it is one of the strongest predictors of changes in travel intensity both during the full lockdown and in the reopening period.[5]

Travel intensity overall fell enormously throughout King County during the lockdown, but it declined particularly sharply in neighborhoods with high average levels of education. Panel (a) of Figure 1 shows the percent change in the SafeGraph measure of travel intensity between February and April as well as between February and July across CBGs in King County. The average decline between February and April across all CBGs in the county was 57%, but this average masks substantial heterogeneity. The more lightly shaded areas had larger reductions in overall travel intensity as measured by cell phone location tracking. The lighter areas are concentrated in northern King County, where more highly educated and higher-income households reside. Mobility recovered slightly after April; the average decline in decline in travel intensity between February and July was 36%. However, comparing the two maps in Panel (a) of Figure 1, it is clear that there is substantial persistence in which locations experienced larger and smaller changes in travel behavior.

Panel (b) of Figure 1 correlates the percent change in travel intensity among residents

[4]The number of devices per resident in a CBG is correlated with neither median income ($r = 0.01$) nor fraction white ($r = 0.02$). The fraction with a bachelor's degree has a slightly greater, but still weak, negative correlation with devices per person ($r = 0.19$). See the scatterplot in Appendix Figure A.1. Squire (2019) demonstrates that the SafeGraph data are representative across multiple demographic dimensions. Squire (2019) also shows that nationwide, typically due to misattribution of home CBGs, a small number of CBGs have an excessive number of devices. Our results are robust to excluding CBGs in which the number of devices per person is more than two standard deviations above the mean.

[5]We run a LASSO model for a cross-section of CBGs with the percent change in travel intensity as the outcome and various CBG characteristics as predictors. The full list of CBG characteristics we use as predictors appears in the notes to Table 1. We select the LASSO penalty parameter using the data-driven rule in Belloni et al. (2012). For both the change in travel intensity between February and April and the change between February and July, only the share of residents with a college degree and some occupation shares survive the LASSO.

of a CBG between February and April as well as between February and July with the fraction of that CBG's residents that have a bachelor's degree. Here and in what follows, we use the 2014-2018 American Community Survey (ACS) for information on socioeconomic characteristics of CBGs. The figures in Panel (b) further highlight the degree to which travel recovered between April and July. They also indicate that, regardless of the time horizon, the decline in overall mobility among residents of less-educated CBGs is substantially smaller in magnitude than the decline among residents of more-educated CBGs. That is, the largest declines in mobility have been persistently concentrated in more-educated neighborhoods.

Table 1 quantifies the relationship between neighborhood education levels and travel declines for the February-July period.[6] Column (1) shows the raw correlation. A CBG where 10% of the residents have a bachelor's degree sees on average a 23% decline in overall mobility between February and July, whereas a CBG where 90% of residents have a bachelor's degree sees on average a 48% decline. As column (2) of Table 1 shows, we find a similar relationship with CBG income levels; every additional $100,000 in median income in a CBG is associated with an 8.6 percentage point larger decline in mobility.[7] Moreover, this correlation is new; Appendix Figure A.2 shows no relationship between neighborhood education level and the January-February change in travel.

As we discuss further in Section 3, we find in column (3) of Table 1 that controlling for characteristics directly related to remote work capabilities (including the share of workers in each of 25 different occupations as well as the share of households with access to a computer, a smartphone, and the internet) sharply attenuates the relationship between neighborhood education and reductions in travel. Additional CBG characteristics beyond these remote work controls explain little of the remaining relationship between education and travel behavior, as shown in column (4). As we also discuss later, we find in column (5) of Table 1 that much of the differentially large mobility response among more-educated neighborhoods

[6] Results for intervening months appear in Appendix Tables A.2 through A.5. Using data up through August 21, we also show results for the February-August change in Appendix Table A.7.

[7] Results are nearly identical if we weight the regressions by CBG population. Results are also very similar if we weight each CBG by the number of SafeGraph devices that reside there.

was concentrated on weekdays.

2.3 Changes in Public Transportation Use

2.3.1 Neighborhood-Level Measures of Transit Use

We take advantage of King County Metro automated passenger counter (APC) data to study changes in public transit use across neighborhoods. The APC data are based on information collected from sensors installed on a subset (approximately 70%) of buses that run in King County. These sensors track boardings, which we aggregate to CBGs in a manner similar to how SafeGraph data are aggregated. We examine how boardings in each CBG change over time and by neighborhood characteristics.

Across CBGs, the average percent decline in transit boardings between February and April was 74%, about a 30% larger decline than that for overall travel during the same period.[8] Moreover, the decline in transit was more persistent; transit use in July remained 63% lower than transit use in February.

Again, the large average decline in transit use across CBGs obscures significant heterogeneity. Figure 2 maps the decline in transit use between February and April as well as between February and July. As with overall travel, high-education neighborhoods in northern King County drive the bulk of reduced transit use in both April and July relative to February. However, as both the maps and scatterplots relating transit use declines and education levels make clear, transit use has recovered less over time than overall travel. Its recovery has also lagged that of overall mobility; the reductions in transit use in May and June relative to February were 74% and 70%, respectively.

Table 2 quantifies the socioeconomic gap in transit use for the February-July period. As shown in column (1) of Table 2, a ten percentage point higher share of residents in a CBG with a bachelor's degree is associated with a 4.3 percentage point larger drop in public transit

[8] Other major cities in the U.S. and around the world experienced very similarly sized drops in public transit use; see Transit (2020).

use between February and July. Replicating the results for overall travel intensity, column (2) of Table 2 documents that the drop in boardings also correlates with income. Every additional \$100,000 in median income in a CBG is associated with a 21 percentage point larger decline in mobility. Notably, and as discussed further below, the socioeconomic gap in transit use reductions are largely explained by differences in remote work capabilities (see column (3) of Table 2). Other CBG demographic characteristics play little additional role in accounting for the gap (column (4)). We also again see that weekday travel declined more than weekend travel among residents of more-educated neighborhoods relative to residents of less-educated neighborhoods (column (5)).

2.3.2 Individual-Level Measures of Transit Use

We obtained administrative data on boardings among King County Metro customers who used transit cards to pay their fares on local public transportation. These cards include regular, adult-fare "ORCA" transit cards (of which there are millions in circulation) as well as reduced-fare "ORCA LIFT" transit cards available only to low-income riders (of which there are over 50,000 in circulation).[9] Taps by ORCA and ORCA LIFT cards allow us to track trips by higher- and lower-income riders separately. However, unlike the APC data, ORCA records omit people who pay by cash or who evade payment.

Notably, King County Metro eliminated fares on all its buses, light rail, and other routes on March 21, 2020 to ensure social distancing protocols among customers and drivers could be maintained. Therefore, we do not have data on taps using ORCA or ORCA LIFT cards after that date.[10]

We see a large overall decline in public transit trips using fare cards as the crisis began to unfold in early March. Again, however, the decline was more marked for higher-

[9] ORCA LIFT cards are available to any household with income less than 200% of the federal poverty line. People enroll in LIFT by requesting a card in-person at public and social service agencies, which verify income prior to issuing the card.

[10] For comparison, we show in Appendix Tables A.2 and A.8 the change in overall travel as measured in the SafeGraph and APC data between February and mid-March.

relative to lower-income riders. Column (1) of Table 3 shows the results. Comparing boardings in February to mid-March (defined as March 11-20), regular ORCA rides fell by 51%, whereas LIFT rides fell by only 32%. Hence, these individual-level data corroborate the neighborhood-level data in showing a sharply heterogeneous mobility response to COVID-19 by socioeconomic group. As columns (2) and (3) of Table 3 show, and as we discuss further below, the differentials are largely driven by changes in ridership within Metro routes as opposed to between metro routes, and weekday use among LIFT riders is particularly high relative to non-LIFT riders during in the early days of the pandemic.

3 Mechanisms

Overall travel intensity fell more sharply for residents of high-education than low-education neighborhoods in the face of the COVID-19 pandemic in King County. Measured changes in public transportation use were particularly large among more highly educated and higher-income individuals. The large disparities in travel behavior across socioeconomic groups that emerged at the onset of the pandemic have persisted well into the reopening period. We next turn to a deeper investigation of potential mechanisms underlying the differences in travel responses to COVID-19 across socioeconomic groups.

3.1 Reliance on Different Modes

We first consider the role of transportation mode substitution during the COVID-19 crisis. From a distributional perspective, examining transportation mode is important for at least two reasons. First, low-income people tend to rely more heavily on public transit (Glaeser et al. 2008). Second, COVID-19 itself and policy responses to it may differentially affect travel by transit versus other modes. Transit may be perceived to be more likely to facilitate viral transmission, which could lead people to avoid it during a pandemic. To the extent that high-income individuals have greater access to means of transportation other than public transit, mode substitution as an avoidance strategy may be more feasible for those individuals. In that case, we would expect to see a larger decline in public transit use than in overall travel for high-income individuals than we see for low-income individuals.

A key result from above is that transit use decreased more and has remained at low levels for longer than travel overall. Thus, in light of the fact that less-educated and lower-income individuals rely disproportionately on public transit, reliance on different modes alone cannot explain the overall mobility gap that emerges during the crisis between high- and low-income travelers. Instead, the larger decrease in transit use suggests that many individuals engaged in transportation mode substitution (away from public transit and toward cars or other modes) in response to the pandemic.

However, while the degree of mode substitution differed across socioeconomic groups early on in the pandemic, our results indicate that differential mode substitution does not drive differences in travel behavior in subsequent months. Between February and July, a neighborhood where 90% of residents hold bachelor's degrees experienced a 48% decrease in overall mobility compared to an 80% percent decrease in transit boardings. Therefore, transit use is about 67% (1 - 0.80/0.48) more responsive than overall travel in high-education neighborhoods. In a neighborhood where 10% of residents hold bachelor's degrees, transit use is almost twice as responsive as travel overall (a 45% vs. a 23% drop). If anything, the relative drop in transit use is smaller in high-education neighborhoods.[11]

During the transition to lockdown, however, mode substitution did differ by socioeconomic status. Between February and mid-March, transit fell by 49% more than travel overall in high-education neighborhoods (64% vs. 43%). Transit fell by only 21% more than travel overall in low-education neighborhoods during the same period (23% vs. 19%).[12] Thus, individuals in high-education neighborhoods substituted away from transit to other modes of travel more than individuals in low-education neighborhoods during the early stages of

[11]This analysis assumes that the average number of other CBGs visited on transit by residents of a CBG is proportional to the number of transit boardings in the CBG.

[12]See Appendix Tables A.2 and A.8 for the results underlying these calculations.

the shutdown. However, this gap disappeared or even reversed as the crisis continued.

3.2 Supply of Public Transportation

One possible explanation for the differences in the magnitudes of the decline in overall travel intensity, and in public transit use in particular, between higher- and lower-income King County residents are public transit service adjustments. Unlike other forms of transportation, policymakers directly control the volume of transit by mapping routes and setting service frequency. In the face of the pandemic, King County Metro limited service in various parts of its system. King County Metro announced its first reductions in service on March 23, 2020. By mid-April, Metro had made three rounds of service adjustments; at that point, Metro was operating 27% fewer service trips than typical weekday service (Switzer 2020). Policy decisions could drive differences in travel behavior if they leave open bus lines in low-income neighborhoods that rely on transit while closing them elsewhere. Transit also requires a minimum volume to operate efficiently; even a reduction in service responding to lower passenger volume during a lockdown could amplify any differences across neighborhoods that appear for other reasons.

While service changes may have reduced transit ridership, we find no evidence that this widened the gap in travel behavior between higher- and lower-income riders. A key advantage of our transit data is that we can compare how full-fare ORCA and low-income LIFT riders *who ride the same route* respond to COVID-19. If a reduced supply of transit drives lower passenger volume, then higher- and lower-income riders on the same route should respond similarly. Figure 3 displays these data. Each circle in the figure represents a Metro route, with bigger circles corresponding to more popular routes. The figure plots the percent change in LIFT boardings on each route between February and mid-March against the percent change in full-fare boardings on the same route during the same period. Nearly all routes are below the 45 degree line, indicating that high-income boardings decrease more than low-income boardings within routes. Formally, as shown in column (1) of Table 3, when we control for route fixed effects in a regression of the percent change in boardings on a LIFT dummy, the coefficient of the LIFT dummy does not change statistically and actually increases in magnitude slightly. This implies that variation across neighborhoods in the impacts of public transit service reductions do not drive the disparities in changes in transit use across socioeconomic groups.[13]

3.3 Remote Work and Commuting

Constraints on lower-income individuals' ability to work remotely could limit their decline in travel. According to Dingel and Neiman (2020), approximately 42% of Seattle area jobs can be performed at home. Mongey et al. (2020) find that nationwide, jobs that do not permit working remotely and jobs that involve high physical proximity tend to be held by individuals that are less educated, have lower income, and are more credit constrained. A disproportionate number of less-educated residents could also be commuting to work at businesses deemed essential and permitted to stay open during the lockdown.[14] Kearney and Pardue (2020) find that, due to essential business exceptions, lower-educated and minority workers are disproportionately likely to be traveling to work during city lockdowns relative to working from home.

We find four pieces of evidence suggesting that differential degrees of remote working across socioeconomic groups represent an important mechanism driving differences in travel behavior during COVID-19, especially at the pandemic's onset and after the most stringent restrictions were relaxed.

[13]Transit service reductions in King County were almost entirely effected by route eliminations and frequency changes as opposed to route adjustments. While changes in stop locations within routes are not a likely source of differences in transit use reductions across socioeconomic groups, to the extent that higher- and lower-income riders were differentially affected by frequency changes, that could contribute to observed disparities. The most likely concern is that differing service reductions by time of day create the gap. However, we show in Appendix Table A.16 that the results remain within any given time of day.

[14]For information on which types of businesses were deemed essential, see https://coronavirus.wa.gov/what-you-need-know/whats-open-and-closed/essential-business.

3.3.1 Proxies for Remote Work Capabilities

Dingel and Neiman (2020), Baker (2020), Koren and Peto (2020), Su (2020) and others have estimated the fraction of jobs that can be performed at home. These papers suggest that remote work capabilities can be well-proxied by occupation. In order to test the extent to which differences in travel behavior between more- and less-educated individuals directly reflect differences in their abilities to perform jobs remotely, we construct CBG-level occupational composition measures from the 2014-2018 ACS. We include the fraction of workers in each of 25 different occupations as well as the fraction of households with access to a computer, a smartphone, and the internet in our previous regressions relating changes in mobility to education levels across neighborhoods.[15] To the extent that more- and less-educated people who have different jobs within our occupational categories can perform work at home at different rates, we will underestimate the role of remote work in explaining the socioeconomic gap in travel behavior.

The results including remote work controls appear in column (3) of both Table 1 and Table 2. In each case, controlling for occupational mix and measures of technology access sharply attenuates the estimated relationship between education and mobility changes between February and July; inclusion of these measures alone reduces the estimated coefficient on fraction with a bachelor's degree by 29% for overall mobility and by 70% for public transit use. Adding a rich set of additional demographic characteristics of each CBG (column (4) of each table; see the table notes and Appendix Table A.1 for a list of these controls) does little to further attenuate the estimated coefficient on the fraction with a bachelor's degree. These results suggest that remote work capabilities explain a large fraction of the socioeconomic

[15] These are the most detailed occupation information available at the CBG level in the ACS. The 25 occupations include management; business and financial operations; computer and mathematical; architecture and engineering; life, physical, and social science; community and social service; legal; educational instruction and library; arts, design, entertainment, sports, and media; health diagnosing and treating practitioners and other related technical; health technologists and technicians; healthcare support; firefighting and prevention, and other protective service; law enforcement workers; food preparation and serving related; building and grounds cleaning and maintenance; personal care and service; sales and related; office and administrative support; farming, fishing, and forestry; construction and extraction; installation, maintenance, and repair; production; transportation; and material moving.

gap in travel behavior in months following the pandemic.

Interestingly, however, we find that remote work opportunities play the largest role in explaining differences in travel behavior when the most stringent restrictions were either being phased in or had begun to be relaxed. At the onset of the pandemic in mid-March and April, our proxies for remote work opportunities explain 30-40% of the estimated relationship between fraction with a bachelor's degree and reductions in overall travel. That fell to about 25% in May and June before increasing back to 29% in July and 48% in the first half of August (see Appendix Tables A.2-A.7). As the pandemic intensified and movement was severely constrained, our remote work controls may have played a more limited role in explaining socioeconomic disparities in travel behavior since most physical work sites were closed. However, as these restrictions began to be relaxed in late June and more businesses opened, remote work capabilities started to play a larger role in explaining the socioeconomic gap in mobility. In the more recent period, those who can perform their jobs at home have continued to do so while those who cannot have begun to commute more regularly.

3.3.2 Weekly Travel Cycles

A second piece of evidence pointing to the importance of commuting for work in explaining socioeconomic disparities in travel is the weekly cycle of travel. The regular weekly cycle of travel attenuates more for high-income people than for low-income people in the aftermath of the crisis. In Panels (a)-(c) of Figure 4, we show daily time series for travel from all three data sources (SafeGraph, APC, and ORCA). For the SafeGraph and APC data, we break out the data based on whether a CBG's share of residents with a bachelor's degree is above versus below the median share. For the ORCA data, we split results based on whether the card used is a full-fare ORCA card or a reduced-fare LIFT card.

Based on the SafeGraph data (Panel (a) of Figure 4), prior to March, daily travel among residents of more- and less-educated CBGs tracks closely. In early March, however, travel begins to taper, particularly among residents of more-educated CBGs. This tapering began soon after the Life Care Center Outbreak was detected in late February and as local social distancing directives were issued, but well before all schools closed and the state's stay-at-home order went into effect. Travel continued to decline, and the gap between residents of more- and less-educated areas continued to grow, as the policy response materialized. Overall travel began to recover in May, but the gap between more- and less-educated neighborhoods remained pronounced well into August.

Most notably, we observe that the pre-COVID-19 weekday versus weekend cycle of trips persists to a greater extent throughout the pandemic period, but particularly during the reopening period, among residents of less-educated CBGs than among residents of more-educated CBGs post-COVID-19. In other words, less-educated and lower-income individuals not only traveled more in general as the COVID-19 crisis wore on, but they traveled more particularly between Mondays and Fridays each week. This suggests that requirements of their jobs contributed to the more muted travel response for these groups. The fact that the weekend travel declines among residents of less-educated neighborhoods more closely matched those of residents of more-educated neighborhoods suggests that differences in travel for recreational purposes is unlikely to be the primary driver behind the overall observed differential decline between groups.

In Panel (b) of Figure 4, we show average daily public transit boardings across CBGs by education level using the APC data. The transit data show a more pronounced weekly pattern than the overall travel data, reflecting the fact that many individuals in King County regularly use transit to get to work but not necessarily for other types of trips. Average boardings per resident are also very similar across high- and low-education neighborhoods prior to March. However, the post-COVID-19 patterns of decline and the growing gap in use between residents of more- versus less-educated CBGs echo those observed in the SafeGraph data. While we see a more modest recovery in transit use relative to overall travel after April, the weekly cycle of public transit boardings remains more conspicuous for residents of lower-education CBGs than for residents of higher-education CBGs, and again particularly so during the reopening period.[16]

We illustrate the time pattern of average boardings per day for ORCA and LIFT cardholders in Panel (c) of Figure 4. The pre-COVID-19 level differences in travel by rider income level are more pronounced in the individual-level data. However, consistent with the SafeGraph and APC data broken out by neighborhood education level, we see an earlier and sharper decline in transit use among regular ORCA cardholders than among LIFT cardholders. Because King County transit authorities eliminated fares on March 21, we do not observe a long post-COVID-19 period in these data. However, the data up to the point of fare elimination corroborate the patterns observed in the two other data sources.

Based on the weekly travel cycles observed in the SafeGraph data, at least 39% of the February-July travel gap between more- and less-educated people can be attributed to work travel. Consider column (5) of Table 1 and neighborhoods with 90% and 10% of residents with bachelor's degrees. The coefficients imply that weekday travel fell by 47% in the high-education neighborhood and 19% in the low-education neighborhood, for a gap of 28%. On the weekend, the difference narrows to 17%. Column (5) of Table 2 and column (3) of Table 3 show similar results for transit boardings as measured by automated passenger counters and ORCA card readers, respectively. Suppose we assume that the weekend effect in the Safegraph data represents the change in travel that happens every day for non-work reasons. Then, a week that experienced this effect every day would have an education gap of 17% on the weekdays, or 61% of the true weekday gap. The other 39% must be due to work travel.

Weekly commuting patterns also point to a larger role for work travel in explaining socioeconomic disparities in travel behavior when restrictions were being phased in and out than when the most severe restrictions were in place. Similar contrasts as above suggest that work travel explained as much as 65% of the socioeconomic differences in travel reductions in mid-March, and 54% in April (see Appendix Tables A.2 and A.3). The share fell to closer

[16] As Appendix Figure A.5 shows, there were no such differential patterns of transit use over time in 2019. Unfortunately, we only have Safegraph data for 2020 and therefore cannot provide the same comparison for Panel (a) of Figure 4.

to 40% between May and July before rising again to 46% in August (see Appendix Tables A.4–A.7).

These estimates of the likely role of work-related travel in explaining the socioeconomic gap in overall travel behavior strongly corroborate those based on including proxies for remote work capabilities. As with the the previous estimates, these are also likely lower bounds for the role of work travel; low-income people are much more likely to work outside regular business hours and on weekends (Shierholz et al. 2012), so the true gap in non-work travel is probably narrower than just what we observe on weekends.

3.3.3 Daily Travel Cycles

A third piece of evidence pointing to remote working as a contributor to disparities in travel behavior are patterns of travel by time of day. These patterns indicate that much of the relatively greater volume of travel among low-income residents of King County is occurring at times at which people are typically travelling to and from work.

Panels (d)-(f) of Figure 4 use the SafeGraph, APC, and ORCA data to illustrate the times of day people travel, broken out by month and by education level of the neighborhood (for the SafeGraph and APC data) or by income of the rider (for the ORCA data).[17] In Panel (d), there is a clear hourly pattern of travel among residents of both higher- and lower-educated neighborhoods in February; the fraction of devices not observed in their home CBG rises from around 40% to near 80% within the span of a few hours each morning, then gradually falls back to 40% beginning in the late afternoon. Both lines flatten substantially by April, but more so for residents of more-educated neighborhoods. Since reopening began, travel during the day has recovered slightly, but in contrast to the pre-COVID-19 period, the fraction of devices not at home during regular work hours remains markedly lower in more-educated than less-educated neighborhoods in July. Moreover, in April as well as July, there remains a more evident hourly pattern of travel for residents of less-educated neighborhoods,

[17]For these figures, we average data over only weekdays. Results are very similar if we include weekends.

particularly during peak evening travel hours.[18]

Similar but even more pronounced changes in travel within days are evident in the APC and ORCA data for public transit use (Panels (e) and (f) of Figure 4). Transit use fell by less, and retained more of its regular daily pattern, for residents of less-educated neighborhoods than for residents of more-educated neighborhoods.

3.3.4 Survey Results

As a fourth and final piece of evidence, we lean on direct survey responses of low-income transit riders. We were in the process of conducting a transit-related survey among low-income residents of King County when the COVID-19 pandemic emerged (Brough et al. 2020a). The survey was given to individuals who agreed to participate in a study in which they had a chance of receiving free transit fares for a limited period of time. The eligible population included those who visited a Washington State Department of Social and Health Services office in King County and who qualified for any public assistance program (e.g., SNAP, Medicaid, or TANF). Between December and March, 1,318 individuals enrolled in our study and provided details about their travel intentions in our intake survey. An additional 185 individuals completed follow-up web and phone surveys conducted between late March and early August that included a travel diary for the previous day's trips.[19]

Between late February and mid-March, as the COVID-19 crisis began, low-income individuals consistently reported intentions to take trips on transit for essential activities even as intentions to take trips on transit for other purposes diminished. All respondents to our intake survey reported the activities for which they expected to use the study transit card; they were allowed to pick multiple items. We categorize these items into essential (work, school, public benefits, and health), commercial (shopping and errands), social (recreation, family, and religious/community), and other activities. Panel (a) of Figure 5 shows how the average number of activities the person selects in each category varies with the time of

[18] Appendix Tables A.14 and A.15 quantify these comparisons in a regression framework.

[19] Appendix Table A.17 provides descriptive statistics for these samples.

the report (which is tied to the timing of their public benefits office visit and enrollment in the study). During the first two months of 2020, all types of trips remain roughly constant. At the onset of COVID-19, intentions to use transit for essential trips remain steady, but intentions to use transit for commercial and social trips trail off.

Meanwhile, follow-up survey responses about travel behavior show all forms of trips declining as policies restricting movement went into effect in late March and April, but work travel rebounding during the first phases of re-opening. While the small sample, low response rate (17%), and self-selection into responding make it important to not overemphasize these results, the 185 respondents to our follow-up surveys are similar on observable characteristics to the full sample (see Appendix Table A.17), and their travel diaries offer a glimpse into the stated purposes of actual travel in the depths of the lockdown as well as during the reopening period. For these diaries, respondents provided the purpose of up to three randomly selected trips taken on the day prior to the web or phone follow-up survey being conducted. These trips are categorized the same way as for the intake survey.

Panel (b) of Figure 5 shows the number of trips from the prior day by the purpose of the trip over time. Trips for shopping and social reasons generally decline throughout the shutdown period. However, work trips decline sharply after the stay-at-home order and recover only after loosening of restrictions at the start of Phase 2 reopening in late June. While only suggestive, these results are consistent with the idea that full lockdown policies restrict commuting for everyone but that partial lockdown policies disproportionately allow movement of low-wage workers, creating socioeconomic gaps in travel behavior.

4 Conclusion

In this paper, we examine socioeconomic differences in travel behavior during the COVID-19 pandemic in King County, Washington. Taking advantage of rich administrative data, we document large average declines in travel, and transit use in particular, in response to the pandemic and associated policy responses. However, the average declines mask substantial heterogeneity across socioeconomic groups. Even after accounting for mode substitution and differential public transit service reductions, travel intensity declined less among less-educated and low-income individuals. Using a combination of administrative and survey data, we trace a large and growing portion of the gap in travel behavior between groups to the relative inability of less-educated and lower-income individuals to perform their jobs from home.

We add to the expanding body of research documenting the disparate, and largely regressive, impacts of the COVID-19 crisis. Our results echo recent findings on, for example, the relatively worse health and labor market impacts of the COVID-19 pandemic for less-educated and lower-income individuals (Abedi et al. 2020, Cajner et al. 2020, Montenovo et al. 2020). The disparities in travel behavior we identify in this paper could be both a cause and consequence of differences across socioeconomic groups in these other outcomes. A higher propensity to travel away from home during the pandemic could contribute to a greater prevalence of the virus among certain groups. Meanwhile, differential abilities to work remotely as an avoidance strategy could generate differences in travel behavior along education and income lines.

Notably, our results pertain to King County, which is home to a major city. They may not generalize to other settings, and in particular to rural areas with limited public transit options. Nonetheless, our findings have important immediate and longer-term policy implications. Our results imply that policies regarding which types of businesses may reopen and when during a pandemic will have meaningful effects on the travel behavior of different socioeconomic groups. Pandemic mitigation policies targeting work-related travel (e.g., those that increase the opportunity cost of traveling to work) are likely to reduce socioeconomic disparities in mobility and possibly also disparities in disease exposure. Notably, however, differences in the ability to perform jobs at home does not explain the entire the gap in travel behavior across socioeconomic groups. This could reflect differential messaging or degrees of compliance with directives regarding non-essential travel.

Our findings also may presage possible shifts in transportation modes and broader changes in mobility patterns as local economies emerge from the COVID-19 crisis. The movement away from public transit may augur increases in road congestion and pollution as economic activity further ramps up. As we have transitioned from complete lockdown to the reopening period, we have also witnessed a persistent gap in travel behavior across socioeconomic groups that is increasingly attributable to differences in remote work capabilities. To the extent that remote working becomes a permanent fixture for some companies, it could mitigate traffic congestion but also cement disparities in travel behavior across socioeconomic groups if those companies tend to have relatively highly educated and high-income workforces.

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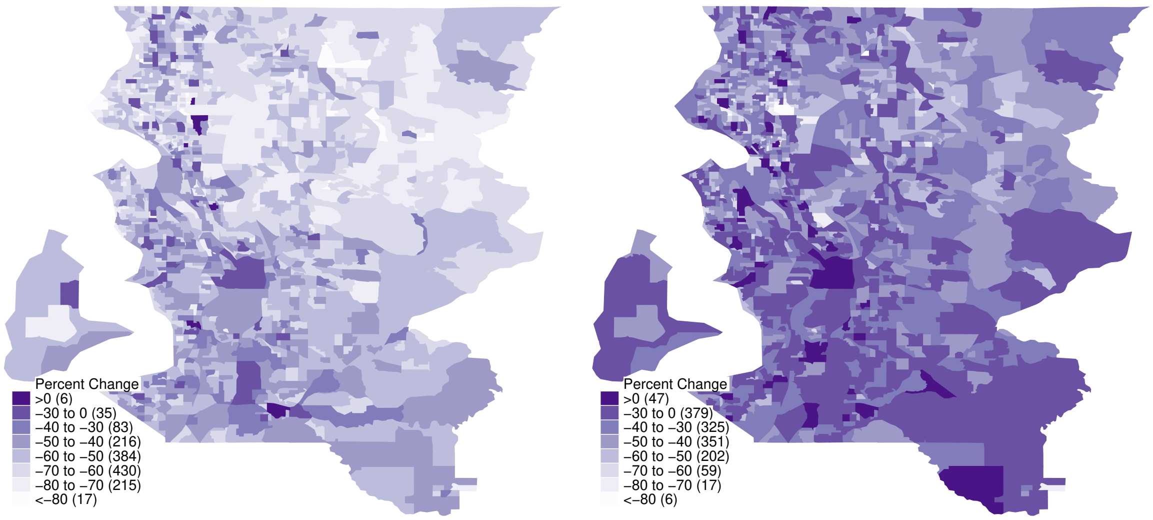
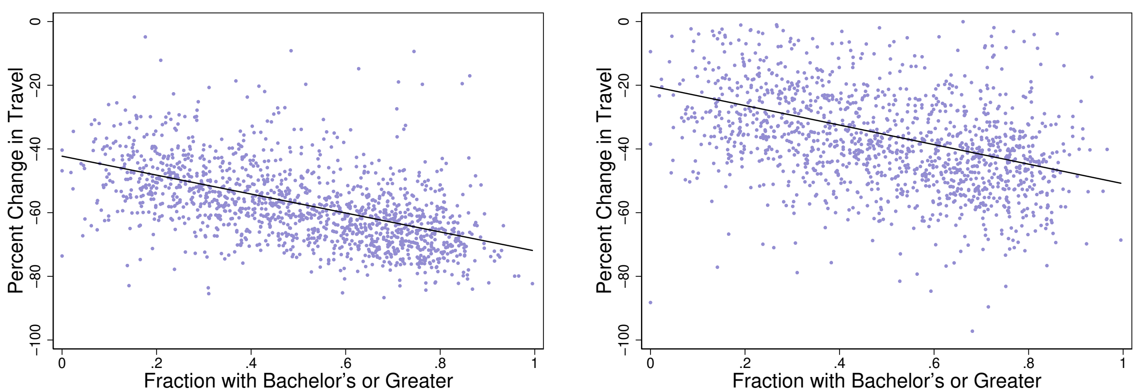
Figures and Tables

(a) Map of King County, Washington



Change in Travel, February-April 2020 Change in Travel, February-July 2020

(b) Correlation with Neighborhood Education

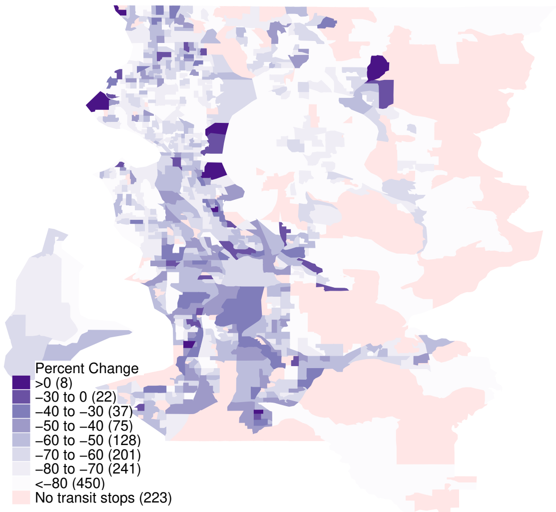


Change in Travel, February-April 2020 Change in Travel, February-July 2020

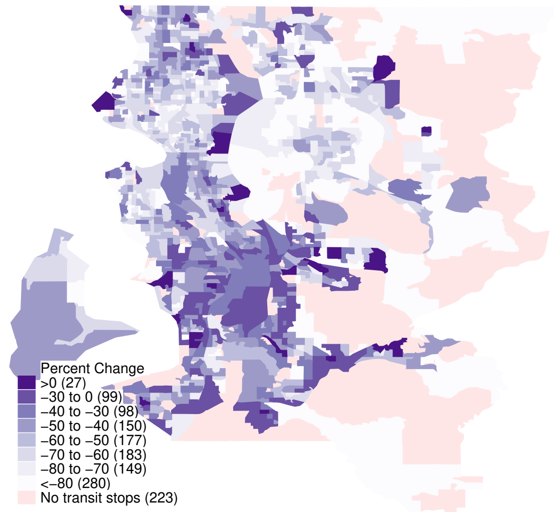
Figure 1. Changes in Travel Intensity during the Pandemic, by Census Block Group

Notes: The unit of observation is a census block group (CBG). Travel intensity is the number of other CBGs visited per device that usually resides in a given CBG, as measured by the SafeGraph Social Distancing Metrics dataset. Fraction with a bachelor's degree comes from the 2014-2018 5-year ACS estimates. To aid with presentation, some CBGs in eastern King County are omitted from the map, and a small number of CBGs with positive change in travel are omitted from the scatterplot. The fitted lines in (c) and (d) reflect all CBG data. Maps showing all CBGs in the county also appear in Appendix Figure A.3.

(a) Map of King County, Washington



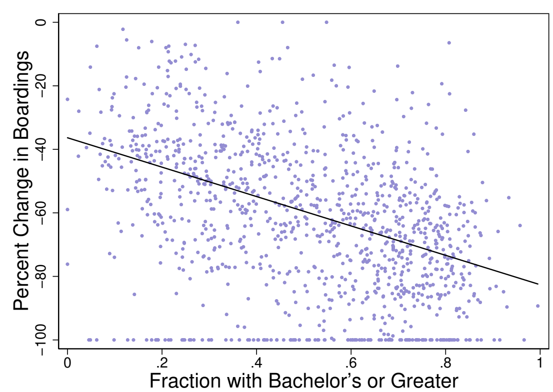
Change in Transit Boardings, February-April 2020



Change in Transit Boardings, February-July 2020

(b) Correlation with Neighborhood Education

Change in Transit Boardings, February-April 2020



Change in Transit Boardings, February-July 2020

Figure 2. Changes in Transit Boardings during the Pandemic, by Census Block Group
Notes: The unit of observation is a census block group (CBG). Boardings come from King County Metro and are measured by automated passenger counters. Fraction with a bachelor's degree comes from the 2014-2018 5-year ACS estimates. To aid with presentation, some CBGs in eastern King County are omitted from the map, and a small number of CBGs with positive change in travel are omitted from the scatterplot. The fitted lines in (c) and (d) reflect all CBG data. Maps showing all CBGs in the county also appear in Appendix Figure A.4.

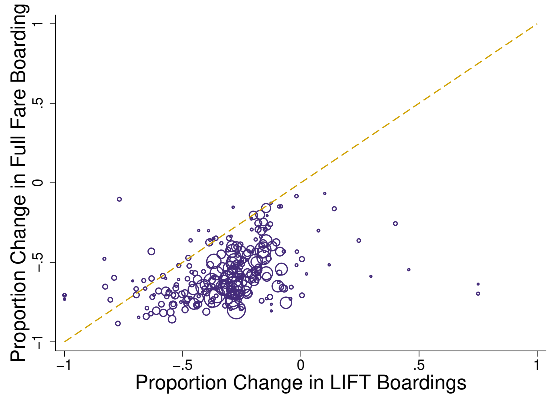
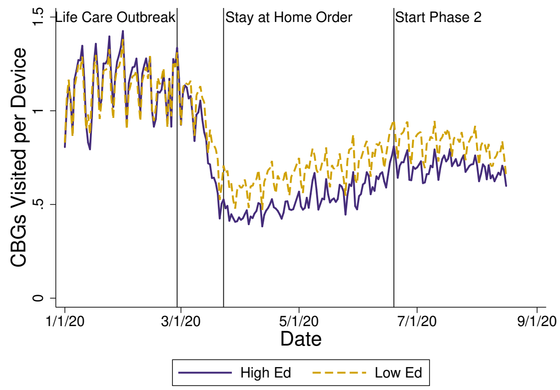
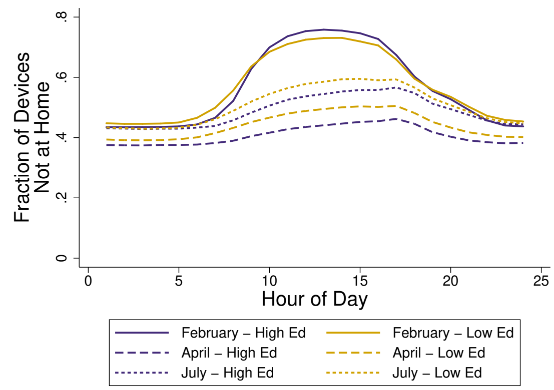


Figure 3. Changes in ORCA Boardings by Route, Base vs. Low-Income Fare

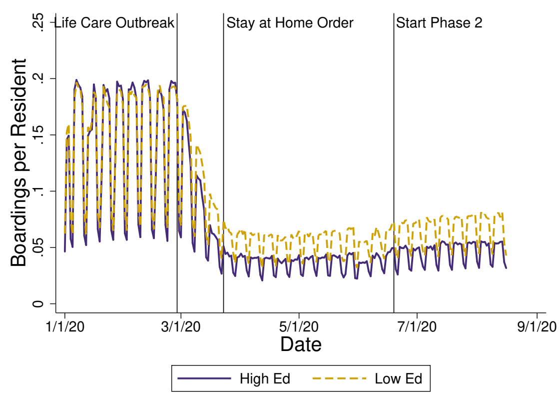
Notes: The unit of observation is a King County Metro route (almost always a bus route). The outcome includes only boardings paid for with an ORCA card, excluding cash and non-payment. Proportion changes compare March 11-20 to February 2020 boardings. Reduced-fare LIFT versus full-fare boardings are detected by the payment type, which depends on the card serial number. The size of the circle is proportional to the sum of LIFT and full-fare boardings on a route in February 2020. We exclude routes that average fewer than 50 boardings per day in February 2020.



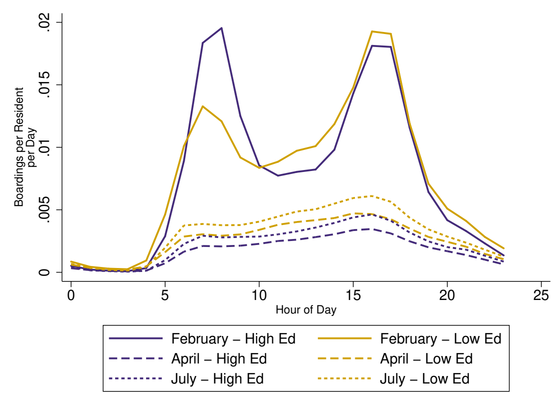
(a) Overall Travel by Nbd Education and Date



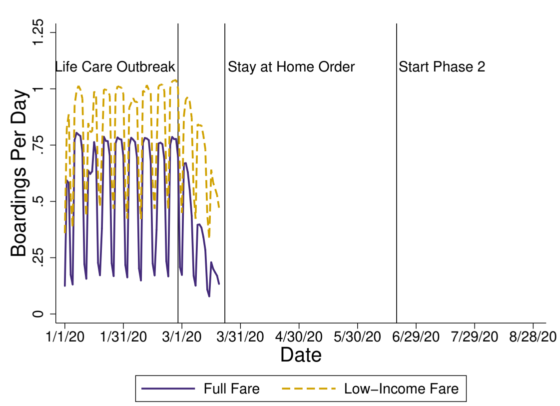
(d) Overall Travel by Nbd Education and Hour



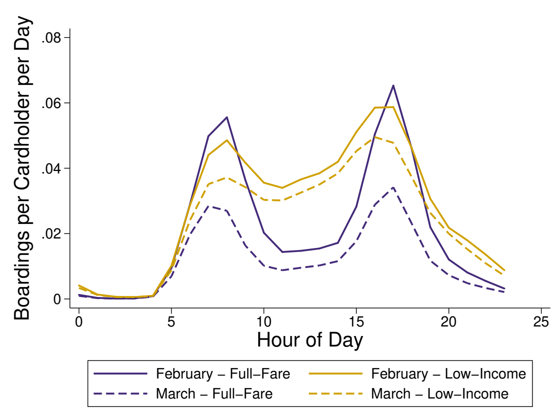
(b) Transit Boardings by Nbd Education and Date



(e) Transit Boardings by Nbd Education and Hour



(c) Transit Boardings by Fare Type and Date



(f) Transit Boardings by Fare Type and Hour

Figure 4. Daily and Hourly Time Series of Travel in King County

Notes: The left column shows daily travel for all days and the right column shows hourly travel averaged over all weekdays in a month. Panels (a), (b), (d), and (e) compare census block groups (CBGs) based on whether they are above or below median for fraction with a bachelor's degree in the 2014-2018 American Community Survey (ACS). Panels (a) and (d) use SafeGraph data on cell phone locations to track CBG visits per device and the fraction of devices not observed in their home CBG. Panels (b) and (e) show the same neighborhood comparison for transit boardings measured by automated passenger counters per 2014-2018 ACS population. Panels (c) and (f) show ORCA card boardings per card by whether the fare charged is the full adult fare or a reduced LIFT fare; the denominator is the number of cards ever used for that type of fare in January-March 2020.

(a) Intended Transit Travel Based on Intake Survey (b) Actual Travel Based on Follow-Up Survey

Figure 5. Intended and Actual Destinations of Low-Income Survey Respondents over Time

Notes: The data come from intake and follow-up surveys for an ongoing study that provides subsidized transit fares (Brough et al. 2020a). In Panel (a), respondents state the purposes for which they intend to use a transit subsidy at time of study enrollment. The outcome shown in the graph is the average number of items selected in that category for respondents completing the intake survey on a given day. In Panel (b), respondents state the purpose of up to three randomly selected trips taken on the day prior to the web or phone follow-up survey being conducted. Panel (a) graphs raw daily averages for the 1318 individuals who completed the intake survey. Panel (b) presents smoothed values from a kernel-weighted local polynomial regression using an Epanechnikov kernel and a bandwidth of 15 days for the 185 individuals who completed a follow-up survey. See Appendix Table A.17 for additional descriptive statistics for these samples.

Table 1. Correlates of Proportion Change in Travel from a CBG, July vs. February, SafeGraph

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.31***		-0.22***	-0.18**	-0.21***
	(0.025)		(0.067)	(0.076)	(0.023)
Median Income ($100k)		-0.086***		0.0090	
		(0.013)		(0.025)	
Weekday					0.15***
					(0.0066)
Weekday × Fraction Bachelor's					-0.13***
					(0.011)
Constant	-0.20***	-0.27***	0.0013	-0.59*	-0.31***
	(0.015)	(0.016)	(0.34)	(0.35)	(0.013)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.36	-0.36	-0.36	-0.36	-0.36
R^2	0.064	0.018	0.078	0.092	0.084
N	43462	43462	43462	43462	43462

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS). The unit of observation is the CBG-day. The dependent variable in each column, which is derived from the SafeGraph Social Distancing Metrics dataset, is the percent change between February and July (divided by 100) in the number of other CBGs visited per device usually residing in the CBG. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table 2. Correlates of Proportion Change in Transit Boardings from a CBG, July vs. February, APC Data

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.43***		-0.13*	-0.10	-0.33***
	(0.033)		(0.078)	(0.089)	(0.031)
Median Income ($100k)		-0.21***		-0.056	
		(0.017)		(0.035)	
Weekday					0.23***
					(0.017)
Weekday × Fraction Bachelor's					-0.14***
					(0.029)
Constant	-0.41***	-0.42***	-0.24	0.057	-0.57***
	(0.020)	(0.018)	(0.20)	(0.29)	(0.020)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.63	-0.63	-0.63	-0.63	-0.63
R^2	0.040	0.033	0.051	0.063	0.061
N	35805	35805	35805	35805	35805

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS) and with at least one transit stop with positive boardings in February 2020. The unit of observation is the CBG-day. The dependent variable in each column is the percent change between February and July (divided by 100) in the number of transit boardings measured by King County Metro's automated passenger counters. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table 3. Correlates of Proportion Change in Transit Boardings, Mid-March vs. February, ORCA Boardings

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel
LIFT	0.19***	0.24***	0.11***
	(0.037)	(0.035)	(0.030)
Weekday			0.40***
			(0.046)
LIFT × Weekday			0.10**
			(0.052)
Constant	-0.51***	-0.49***	-0.83***
	(0.022)	(0.018)	(0.042)
Route FE	No	Yes	No
Mean of Dep. Var.	-0.42	-0.42	-0.42
R^2	0.0072	0.14	0.033
N	6680	6680	6680

Notes: Each column shows results from an OLS regression. The sample includes all "taps" by regular-fare ORCA and reduced-fare ORCA LIFT cards to board public transit in King County in February 2020 and between March 11 and 20, 2020. The unit of observation is the route-day-fare type. The dependent variable in each column is the percent change between February and mid-March (divided by 100) in the number of transit boardings measured by fares paid with each type of fare. Fare types are either the low-income LIFT fare or the full adult fare. Weekday refers to Monday through Friday. Standard errors are clustered by route. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Appendix Figures and Tables

Figure A.1. Correlation of SafeGraph Device Prevalence with Education Levels, by CBG
Notes: The unit of observation is census block group (CBG). Number of devices residing in the CBG is the average over January and February 2020 from the SafeGraph Social Distancing Metrics dataset. Total population and fraction with a bachelor's degree comes from the 2014-2018 5-year ACS estimates.

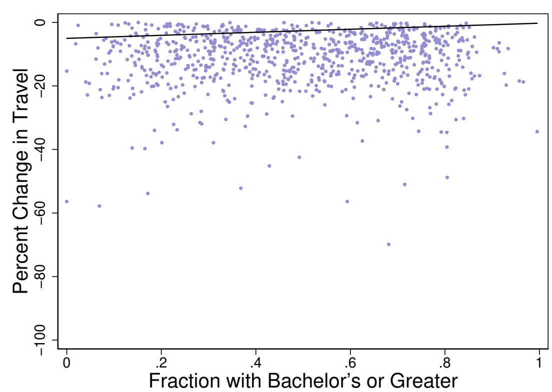
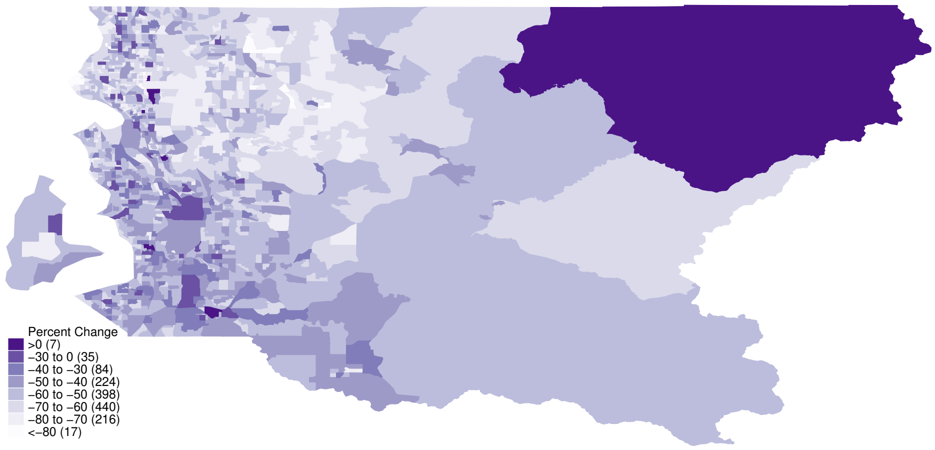
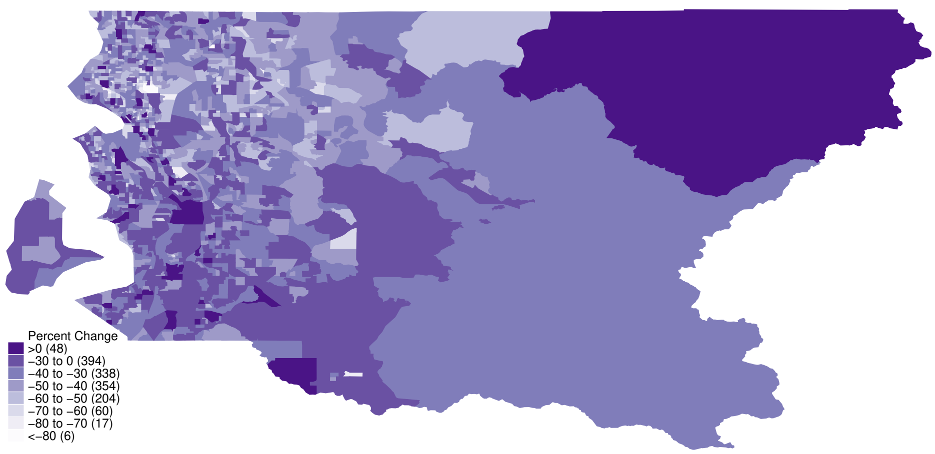


Figure A.2. Percent Change in Travel Intensity between January and February, by Census Block Group
Notes: The unit of observation is census block group (CBG). Travel intensity is the number of other CBGs visited per device that usually resides in the given CBG, as measured by the SafeGraph Social Distancing Metrics dataset. Fraction with a bachelor's degree comes from the 2014-2018 5-year American Community Survey (ACS) estimates. To be consistent with the main text, CBGs with positive change in travel are omitted from the scatterplot.

Map of King County, Washington



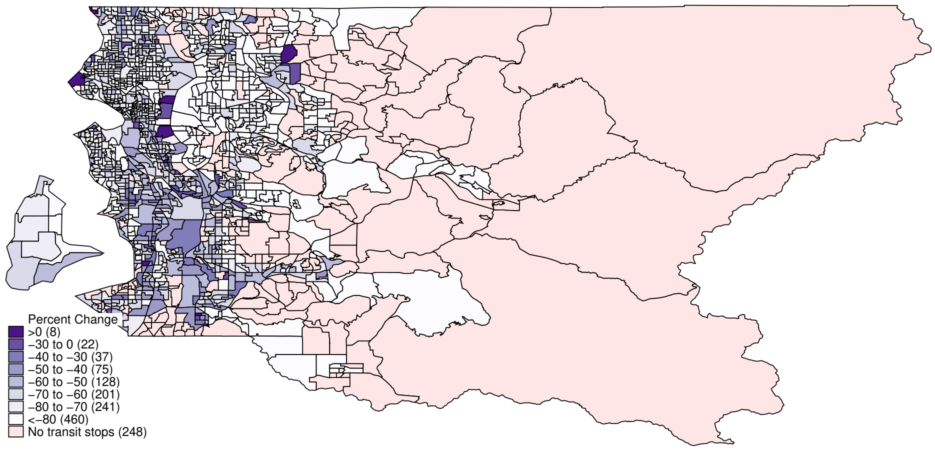
(a) Change in Travel, February-April 2020



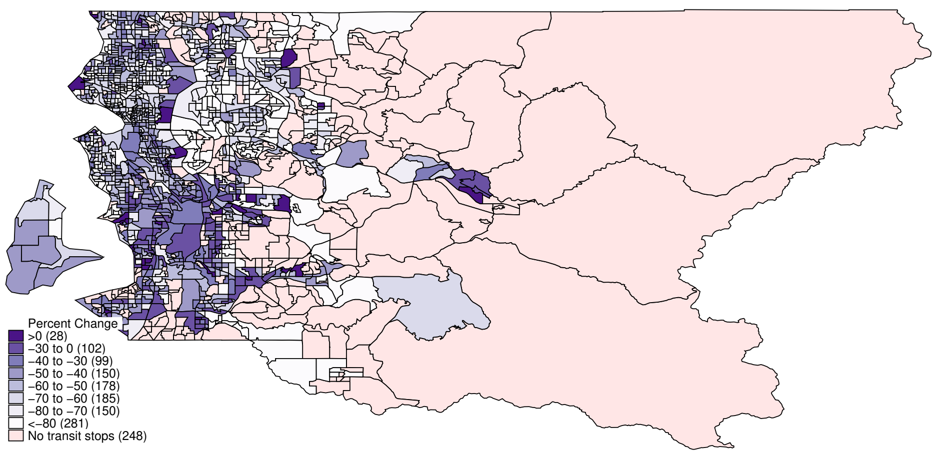
(b) Change in Travel, February-July 2020

Figure A.3. Changes in Travel Intensity during the Pandemic, by Census Block Group
Notes: The unit of observation is census block group (CBG). Travel intensity is the number of other CBGs visited per device that usually resides in the given CBG, as measured by the SafeGraph Social Distancing Metrics dataset.

Map of King County, Washington



(a) Change in Transit Boardings, February-April 2020



(b) Change in Transit Boardings, February-July 2020

Figure A.4. Changes in Transit Boardings during the Pandemic, by Census Block Group
Notes: The unit of observation is census block group (CBG). Boardings come from King County Metro and are measured by automated passenger counters.

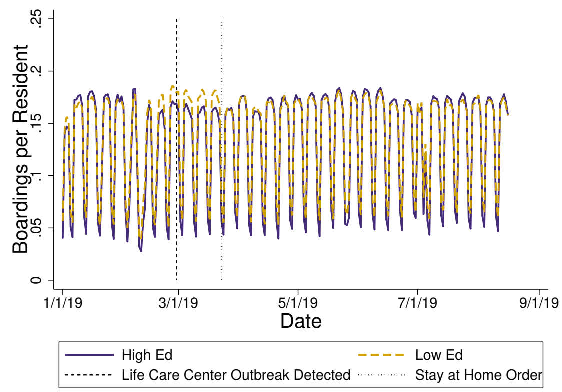


Figure A.5. Transit Boardings by Neighborhood Education and Date, 2019

Notes: The graph shows daily travel comparing census block groups (CBGs) based on whether they are above or below median for fraction with a bachelor's degree in the 2014-2018 American Community Survey (ACS). Transit boardings are based on automated passenger counter (APC) data and are scaled by 2014-2018 ACS population.

Table A.1. King County Census Block Group Descriptive Statistics

	Mean		
	mean	sd	count
Device Count	77.89	55.22	1421
Population	1522.35	593.77	1421
Devices per Person	0.05	0.02	1420
Proportion Male	0.50	0.05	1420
Proportion Minors	0.20	0.08	1420
Proportion Seniors	0.13	0.08	1420
Proportion Moved in Past Year	0.18	0.12	1420
Proportion Commuting 30+ Min	0.49	0.14	1420
Proportion Commuting by Transit	0.14	0.11	1420
Proportion Families	0.64	0.20	1419
Proportion Married Families	0.51	0.20	1419
Proportion Bachelors or Greater	0.50	0.22	1420
Proportion English as Primary Language	0.73	0.16	1419
Proportion Poor	0.09	0.10	1419
Proportion White	0.62	0.21	1420
Proportion Black	0.06	0.09	1420
Proportion American Indiana/Pacific Islander	0.01	0.04	1420
Proportion Asian	0.16	0.14	1420
Propotion Hispanic	0.09	0.10	1420
Median Income	1.00	0.43	1402
Proportion with Public Assistance Income	0.02	0.03	1419
Proportion Employed	0.66	0.10	1420
Proportion in Labor Force	0.70	0.10	1420
Proportion Renters	0.37	0.27	1419
Proportion with Vehicle Available	0.92	0.11	1419
Proportion with Smartphone	0.88	0.08	1419
Proportion with Computer	0.89	0.11	1419
Proportion with Internet	0.91	0.09	1419

Notes: Sample includes census block groups (CBGs) in King County, Washington. Data derived from the 2014-2018 American Community Survey (ACS) and the SafeGraph Social Distancing Metrics dataset.

Table A.2. Correlates of Proportion Change in Travel from a CBG, Mid-March vs. February, SafeGraph

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.30***		-0.21***	-0.19***	-0.12***
	(0.017)		(0.040)	(0.044)	(0.020)
Median Income ($100k)		-0.11***		-0.021	
		(0.0091)		(0.018)	
Weekday					0.14***
					(0.0092)
Weekday × Fraction Bachelor's					-0.23***
					(0.016)
Constant	-0.16***	-0.21***	0.071	0.041	-0.28***
	(0.0095)	(0.011)	(0.14)	(0.19)	(0.011)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.32	-0.32	-0.32	-0.32	-0.32
R^2	0.082	0.040	0.091	0.098	0.092
N	14020	14020	14020	14020	14020

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS). The unit of observation is the CBG-day. The dependent variable in each column, which is derived from the SafeGraph Social Distancing Metrics dataset, is the percent change between February and mid-March (divided by 100) in the number of other CBGs visited per device usually residing in the CBG. Mid-March refers to March 11-20, 2020. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.3. Correlates of Proportion Change in Travel from a CBG, April vs. February, SafeGraph

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.30***		-0.18***	-0.17***	-0.17***
	(0.018)		(0.039)	(0.039)	(0.018)
Median Income ($100k)		-0.13***		-0.020	
		(0.011)		(0.017)	
Weekday					0.13***
					(0.0082)
Weekday × Fraction Bachelor's					-0.18***
					(0.013)
Constant	-0.42***	-0.44***	-0.20	-0.56***	-0.51***
	(0.011)	(0.014)	(0.13)	(0.17)	(0.010)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.57	-0.57	-0.57	-0.57	-0.57
R^2	0.095	0.063	0.11	0.12	0.11
N	39256	39256	39256	39256	39256

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS). The unit of observation is the CBG-day. The dependent variable in each column, which is derived from the SafeGraph Social Distancing Metrics dataset, is the percent change between February and April (divided by 100) in the number of other CBGs visited per device usually residing in the CBG. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.4. Correlates of Proportion Change in Travel from a CBG, May vs. February, SafeGraph

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.36***		-0.27***	-0.26***	-0.25***
	(0.018)		(0.041)	(0.043)	(0.019)
Median Income ($100k)		-0.12***		-0.0081	
		(0.0095)		(0.017)	
Weekday					0.12***
					(0.0052)
Weekday $\times$ Fraction Bachelor's					-0.16***
					(0.0090)
Constant	-0.31***	-0.37***	-0.33**	-0.73***	-0.39***
	(0.011)	(0.012)	(0.13)	(0.18)	(0.011)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.49	-0.49	-0.49	-0.49	-0.49
R^2	0.15	0.060	0.17	0.18	0.17
N	43462	43462	43462	43462	43462

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS). The unit of observation is the CBG-day. The dependent variable in each column, which is derived from the SafeGraph Social Distancing Metrics dataset, is the percent change between February and May (divided by 100) in the number of other CBGs visited per device usually residing in the CBG. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.5. Correlates of Proportion Change in Travel from a CBG, June vs. February, SafeGraph

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.34***		-0.25***	-0.22***	-0.23***
	(0.022)		(0.050)	(0.055)	(0.022)
Median Income ($100k)		-0.095***		-0.0094	
		(0.011)		(0.019)	
Weekday					0.14***
					(0.0056)
Weekday × Fraction Bachelor's					-0.15***
					(0.0096)
Constant	-0.22***	-0.30***	-0.18	-0.70***	-0.32***
	(0.013)	(0.014)	(0.22)	(0.26)	(0.013)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.39	-0.39	-0.39	-0.39	-0.39
R^2	0.10	0.030	0.12	0.14	0.12
N	42060	42060	42060	42060	42060

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS). The unit of observation is the CBG-day. The dependent variable in each column, which is derived from the SafeGraph Social Distancing Metrics dataset, is the percent change between February and June (divided by 100) in the number of other CBGs visited per device usually residing in the CBG. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.6. Correlates of Proportion Change in Travel from a CBG, July vs. February, SafeGraph

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.31***		-0.22***	-0.18**	-0.21***
	(0.025)		(0.067)	(0.076)	(0.023)
Median Income ($100k)		-0.086***		0.0090	
		(0.013)		(0.025)	
Weekday					0.15***
					(0.0066)
Weekday × Fraction Bachelor's					-0.13***
					(0.011)
Constant	-0.20***	-0.27***	0.0013	-0.59*	-0.31***
	(0.015)	(0.016)	(0.34)	(0.35)	(0.013)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.36	-0.36	-0.36	-0.36	-0.36
R^2	0.064	0.018	0.078	0.092	0.084
N	43462	43462	43462	43462	43462

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS). The unit of observation is the CBG-day. The dependent variable in each column, which is derived from the SafeGraph Social Distancing Metrics dataset, is the percent change between February and July (divided by 100) in the number of other CBGs visited per device usually residing in the CBG. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.7. Correlates of Proportion Change in Travel from a CBG, Early August vs. February, SafeGraph

	(1)	(2)	(3)	(4)	(5)
	Chg. in Travel	Chg. in Travel	Chg. in Travel	Chg. in Travel	Chg. in Travel
Fraction Bachelor's	-0.25***		-0.13	-0.097	-0.15***
	(0.035)		(0.095)	(0.10)	(0.034)
Median Income ($100k)		-0.083***		0.014	
		(0.017)		(0.035)	
Weekday					0.12***
					(0.0074)
Weekday × Fraction Bachelor's					-0.13***
					(0.012)
Constant	-0.21***	-0.25***	0.41	-0.099	-0.30***
	(0.019)	(0.022)	(0.53)	(0.52)	(0.020)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.33	-0.33	-0.33	-0.33	-0.33
R^2	0.024	0.010	0.043	0.055	0.030
N	29442	29442	29442	29442	29442

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS). The unit of observation is the CBG-day. The dependent variable in each column, which is derived from the SafeGraph Social Distancing Metrics dataset, is the percent change between February and early August (divided by 100) in the number of other CBGs visited per device usually residing in the CBG. Early August refers to August 1-21, 2020. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.8. Correlates of Proportion Change in Transit Boardings from a CBG, Mid-March vs. February

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.51***		-0.17*	-0.18*	-0.32***
	(0.030)		(0.096)	(0.097)	(0.033)
Median Income ($100k)		-0.19***		0.0011	
		(0.021)		(0.045)	
Weekday					0.43***
					(0.028)
Weekday × Fraction Bachelor's					-0.24***
					(0.041)
Constant	-0.18***	-0.26***	0.044	0.11	-0.53***
	(0.019)	(0.020)	(0.23)	(0.32)	(0.020)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.44	-0.44	-0.44	-0.44	-0.44
R^2	0.026	0.013	0.033	0.036	0.058
N	11550	11550	11550	11550	11550

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS) and with at least one transit stop with positive boardings in February 2020. The unit of observation is the CBG-day. The dependent variable in each column is the percent change between February and mid-March (divided by 100) in the number of transit boardings measured by King County Metro's automated passenger counters. Mid-March refers to March 11-20, 2020. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.9. Correlates of Proportion Change in Transit Boardings from a CBG, April vs. February

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.31***		-0.018	-0.0043	-0.20***
	(0.024)		(0.055)	(0.062)	(0.021)
Median Income ($100k)		-0.17***		-0.026	
		(0.013)		(0.026)	
Weekday					0.20***
					(0.011)
Weekday × Fraction Bachelor's					-0.15***
					(0.019)
Constant	-0.58***	-0.57***	-0.18	-0.044	-0.72***
	(0.014)	(0.014)	(0.16)	(0.22)	(0.013)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.74	-0.74	-0.74	-0.74	-0.74
R^2	0.039	0.041	0.058	0.076	0.063
N	34650	34650	34650	34650	34650

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS) and with at least one transit stop with positive boardings in February 2020. The unit of observation is the CBG-day. The dependent variable in each column is the percent change between February and April (divided by 100) in the number of transit boardings measured by King County Metro's automated passenger counters. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.10. Correlates of Proportion Change in Transit Boardings from a CBG, May vs. February

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.33***		0.016	0.0084	-0.24***
	(0.027)		(0.058)	(0.062)	(0.024)
Median Income ($100k)		-0.18***		-0.0031	
		(0.013)		(0.028)	
Weekday					0.17***
					(0.014)
Weekday × Fraction Bachelor's					-0.13***
					(0.022)
Constant	-0.57***	-0.56***	-0.050	0.21	-0.69***
	(0.016)	(0.015)	(0.20)	(0.29)	(0.015)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.74	-0.74	-0.74	-0.74	-0.74
R^2	0.047	0.050	0.072	0.097	0.071
N	35805	35805	35805	35805	35805

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS) and with at least one transit stop with positive boardings in February 2020. The unit of observation is the CBG-day. The dependent variable in each column is the percent change between February and May (divided by 100) in the number of transit boardings measured by King County Metro's automated passenger counters. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.11. Correlates of Proportion Change in Transit Boardings from a CBG, June vs. February

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.37***		-0.046	-0.040	-0.26***
	(0.028)		(0.064)	(0.072)	(0.025)
Median Income ($100k)		-0.20***		-0.034	
		(0.014)		(0.028)	
Weekday					0.21***
					(0.014)
Weekday × Fraction Bachelor's					-0.16***
					(0.024)
Constant	-0.51***	-0.50***	-0.080	-0.070	-0.66***
	(0.017)	(0.015)	(0.19)	(0.25)	(0.015)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.70	-0.70	-0.70	-0.70	-0.70
R^2	0.051	0.052	0.071	0.091	0.077
N	34650	34650	34650	34650	34650

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS) and with at least one transit stop with positive boardings in February 2020. The unit of observation is the CBG-day. The dependent variable in each column is the percent change between February and June (divided by 100) in the number of transit boardings measured by King County Metro's automated passenger counters. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.12. Correlates of Proportion Change in Transit Boardings from a CBG, July vs. February

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.43***		-0.13*	-0.10	-0.33***
	(0.033)		(0.078)	(0.089)	(0.031)
Median Income ($100k)		-0.21***		-0.056	
		(0.017)		(0.035)	
Weekday					0.23***
					(0.017)
Weekday × Fraction Bachelor's					-0.14***
					(0.029)
Constant	-0.41***	-0.42***	-0.24	0.057	-0.57***
	(0.020)	(0.018)	(0.20)	(0.29)	(0.020)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.63	-0.63	-0.63	-0.63	-0.63
R^2	0.040	0.033	0.051	0.063	0.061
N	35805	35805	35805	35805	35805

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS) and with at least one transit stop with positive boardings in February 2020. The unit of observation is the CBG-day. The dependent variable in each column is the percent change between February and July (divided by 100) in the number of transit boardings measured by King County Metro's automated passenger counters. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.13. Correlates of Proportion Change in Transit Boardings from a CBG, Early August vs. February

	(1) Chg. in Travel	(2) Chg. in Travel	(3) Chg. in Travel	(4) Chg. in Travel	(5) Chg. in Travel
Fraction Bachelor's	-0.50***		-0.16*	-0.18*	-0.37***
	(0.038)		(0.094)	(0.10)	(0.034)
Median Income ($100k)		-0.22***		-0.045	
		(0.018)		(0.039)	
Weekday					0.27***
					(0.022)
Weekday × Fraction Bachelor's					-0.20***
					(0.033)
Constant	-0.36***	-0.40***	-0.15	0.91**	-0.53***
	(0.024)	(0.020)	(0.27)	(0.42)	(0.022)
CBG Computer Characteristics	No	No	Yes	Yes	No
CBG Occupation Shares	No	No	Yes	Yes	No
Other CBG Characteristics	No	No	No	Yes	No
Mean of Dep. Var.	-0.61	-0.61	-0.61	-0.61	-0.61
R^2	0.036	0.026	0.046	0.057	0.055
N	18480	18480	18480	18480	18480

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with complete demographic information in the 2014-2018 American Community Survey (ACS) and with at least one transit stop with positive boardings in February 2020. The unit of observation is the CBG-day. The dependent variable in each column is the percent change between February and early August (divided by 100) in the number of transit boardings measured by King County Metro's automated passenger counters. Early August refers to August 1-21, 2020. Fraction with a bachelor's degree and median income come from the 2014-2018 ACS. Column (3) includes controls for 2014-2018 ACS values for the fraction of households with internet, computer, and smartphone access as well as the fraction of workers in each of 25 different occupations (see text for details). Column (4) includes controls for 2014-2018 ACS values for the fraction of the CBG that is male, under 18, over 65, white, black, American Indian/Pacific Islander, Asian-American, Hispanic, moved in the past year, commuting 30+ minutes, commuting by transit, in families, in families with married head, in poverty, English-speaking, receiving public assistance, renting, employed, in the labor force, and with a vehicle. See Appendix Table A.1 for CBG descriptive statistics. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.14. Proportion Change in Travel from a CBG by Education and Hour, April vs. February, Safegraph

	(1) Peak AM	(2) Peak PM	(3) Midday	(4) Night
Weekday	-0.079***	-0.056***	-0.11***	-0.019***
	(0.0051)	(0.0041)	(0.0044)	(0.0048)
Fraction Bachelor's	-0.071**	-0.15***	-0.20***	-0.040
	(0.029)	(0.025)	(0.025)	(0.029)
Weekday × Fraction Bachelor's	0.094***	0.061***	0.11***	0.029***
	(0.0092)	(0.0073)	(0.0078)	(0.0087)
Constant	-0.24***	-0.27***	-0.30***	-0.23***
	(0.018)	(0.016)	(0.015)	(0.018)
Mean of Dep. Var.	-0.29	-0.36	-0.42	-0.25
R^2	0.0025	0.0094	0.019	0.00039
N	38340	38340	38340	38340

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with educational attainment information in the 2014-2018 American Community Survey (ACS). The unit of observation is the CBG-day. The dependent variable in each column, which is derived from the SafeGraph Social Distancing Metrics dataset, is the percent change between February and April (divided by 100) in the number of other CBGs visited per device usually residing in the CBG. Each column restricts the outcome to travel occurring during a certain time of the day. These time periods are 3-9 AM, 2-7 PM, 9 AM-2 PM, and 7 PM-3 AM. Fraction with a bachelor's degree comes from the 2014-2018 ACS, and weekday refers to Monday through Friday. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.15. Proportion Change in Travel from a CBG by Education and Hour, July vs. February, Safegraph

	(1) Peak AM	(2) Peak PM	(3) Midday	(4) Night
Weekday	-0.088***	-0.063***	-0.13***	-0.012*
	(0.0065)	(0.0055)	(0.0054)	(0.0065)
Fraction Bachelor's	-0.065	-0.14***	-0.21***	-0.0052
	(0.049)	(0.042)	(0.040)	(0.051)
Weekday × Fraction Bachelor's	0.12***	0.074***	0.13***	0.034**
	(0.013)	(0.011)	(0.010)	(0.013)
Constant	-0.097***	-0.10***	-0.13***	-0.083***
	(0.030)	(0.025)	(0.024)	(0.031)
Mean of Dep. Var.	-0.14	-0.18	-0.26	-0.084
R^2	0.0015	0.0054	0.016	0.000067
N	44020	44020	44020	44020

Notes: Each column shows results from an OLS regression. The sample includes all census block groups (CBGs) in King County, WA with educational attainment information in the 2014-2018 American Community Survey (ACS). The unit of observation is the CBG-day. The dependent variable in each column, which is derived from the SafeGraph Social Distancing Metrics dataset, is the percent change between February and July (divided by 100) in the number of other CBGs visited per device usually residing in the CBG. Each column restricts the outcome to travel occurring during a certain time of the day. These time periods are 3-9 AM, 2-7 PM, 9 AM-2 PM, and 7 PM-3 AM. Fraction with a bachelor's degree comes from the 2014-2018 ACS, and weekday refers to Monday through Friday. Standard errors are clustered by CBG. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.16. Proportion Change in Transit Boardings by Hour, Mid-March vs. February, ORCA Boardings

	(1) Peak AM	(2) Peak AM	(3) Peak PM	(4) Peak PM	(5) Midday	(6) Midday	(7) Night	(8) Night
LIFT	0.016	0.043***	0.062***	0.078***	0.10***	0.10***	0.0086	0.014***
	(0.012)	(0.0096)	(0.016)	(0.017)	(0.030)	(0.030)	(0.0083)	(0.0051)
Constant	-0.82***	-0.87***	-0.80***	-0.82***	-0.93***	-0.86***	-0.96***	-0.95***
	(0.0096)	(0.0048)	(0.012)	(0.0084)	(0.0071)	(0.015)	(0.011)	(0.0025)
Route FE	No	Yes	No	Yes	No	Yes	No	Yes
Mean of Dep. Var.	-0.81	-0.81	-0.77	-0.77	-0.88	-0.88	-0.96	-0.96
R^2	0.00041	0.17	0.0024	0.073	0.0056	0.16	0.00012	0.18
N	6680	6680	6680	6680	6680	6680	6680	6680

Notes: Each column shows results from an OLS regression. The sample includes all "taps" by regular-fare ORCA and reduced-fare ORCA LIFT cards to board public transit in King County in February 2020 and between March 11 and 20, 2020. The unit of observation is the route-day-fare type. The dependent variable in each column is the percent change between February and mid-March (divided by 100) in the number of transit boardings measured by taps with each type of fare. Fare types are either the low-income LIFT fare or the full adult fare. Each column restricts the outcome to boardings occurring during a certain time of the day. These time periods are 3-9 AM, 2-7 PM, 9 AM-2 PM, and 7 PM-3 AM. The even columns include route fixed effects. Standard errors are clustered by route. Statistical significance at the 10, 5, and 1 percent level is denoted, respectively, by *, **, and ***.

Table A.17. Descriptive Statistics for Travel Survey

	Completed Intake Survey Mean/SE	***Responded to Follow-Up Survey*** Mean/SE
Intake Survey		
Age	40.4	40.4
	(13.1)	(13.6)
Travel Intention: Number of Essential Destinations	2.00	2.19
	(1.26)	(1.22)
Travel Intention: Number of Commercial Destinations	1.32	1.38
	(0.77)	(0.79)
Travel Intention: Number of Social Destinations	1.39	1.54
	(1.15)	(1.16)
Travel Intention: Number of Other Destinations	0.061	0.043
	(0.24)	(0.20)
Days Used Public Transit in Past Month	15.6	15.8
	(10.9)	(10.9)
Value of a Monthly Transit Pass	14.8	17.3
	(18.9)	(20.2)
Follow-up Survey		
Total Trips Taken		1.97
		(2.19)
Total Trips Taken in Feb		3.05
		(4.18)
Never Left Home		0.37
		(0.48)
Number of Essential Trips		0.49
		(0.95)
Number of Commercial Trips		0.86
		(1.48)
Number of Social Trips		0.62
		(1.36)
Number of Other Trips		0
		(0)
Number of Work Trips		0.25
		(0.65)
Observations	1318	185

Notes: The data come from an ongoing study that provides subsidized transit fares (Brough et al. 2020a). The top panel reports variables from an intake survey. The bottom panel shows variables measured through a phone and web survey conducted 1-3 months later.