Disparities in Mobility Responses to COVID-19

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Abstract

We investigate the role of demographic differences in mobility in explaining disparities in COVID-19 outcomes in New York City. We find: 1) New York City residents in richer neighborhoods are substantially more likely to flee the city, 2) Low-income, black, and Hispanic neighborhoods exhibit more work activity during the day, and 3) these neighborhoods also exhibit less sheltering in place activity during non-work hours. Measured disparities in COVID-19 cases are attenuated after accounting for these mobility responses. Our results point to important inequities in access to sheltering options during pandemics within cities.

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I Introduction

COVID-19 has disproportionally and negatively impacted underprivileged populations. As we document in Figure I, and has been commonly remarked upon in popular press, this pandemic has particularly affected low-income individuals, African-Americans, and Hispanics, with African-Americans suffering as much as 32% of COVID-19 deaths despite making up 13% of the population.[1] While this disproportionate disease burden may reflect long-standing disparities in health outcomes in these communities, it may also reflect novel patterns of mobility and exposure with respect to this new infection.

This paper uses mobile phone Global Positioning System (GPS) data to examine the mobility responses of neighborhoods in New York City affected by COVID-19. We show three key findings regarding differential mobility responses across neighborhoods. First, richer and younger neighborhoods see far greater increases in the propensity of individuals to leave the city, starting around March 14, 2020. These individual moves are well-proxied by networks of Facebook friends in the areas they move to, suggesting that richer and younger New York City residents are able to shelter in second homes and with friends and family away from the epicenter of the outbreak. Second, we find differential patterns of sheltering in place during the pandemic in low-income, black, and Hispanic neighborhoods. This is the case during normal work hours, when it is plausible that members of these populations are likely to be frontline workers, while other populations are more easily able to work remotely. The same is true during non-work hours, when adherence to shelter in place orders may depend on the frequency of visits to retail establishments instead of ordering food and groceries delivery services, or when essential workers might be required to work longer hours.

These findings complement other well-established health disparities which may impact the severity of COVID-19 for different populations, such as in Wong, Shapiro, Boscardin,

[1] See https://www.nytimes.com/2020/04/07/us/coronavirus-race.html and https://www.apmresearchlab.org/covid/deaths-by-race.

and Ettner (2002) and Trivedi, Zaslavsky, Schneider, and Ayanian (2005). We do not argue that mobility patterns are the sole contributing factor to disparities in COVID-19 outcomes, but instead that patterns of mobility may leave more vulnerable populations uniquely exposed to this pandemic.

This work contrasts with existing popular press and literature, which has emphasized the role of population density in isolation as a risk factor for COVID-19. Angel, Blei, Lamson-Hall, and Tamayo (2020) for instance highlights the role of density in explaining cross-city patterns of exposure to COVID-19 infection. Our work emphasizes the role of different mobility patterns within the city. The wealthy may have access to different protective measures against the same baseline levels of population density. The flexibility to work remotely allows individuals to limit outdoor physical presence and more readily leave the city to shelter with friends and family, second homes provide protective insurance against continued presence in the city, and access to additional delivery options may improve adherence to stay-in-place orders.

Our work is most closely related to Almagro and Orane-Hutchinson (2020) which links demographic exposure in New York City to COVID-19 case loads. This work provides more direct evidence on physical presence channels linking occupational type and COVID-19 outcomes, incorporates behavioral responses outside of work hours, and adds evidence on extensive margin responses of leaving the city. Our work is also closely linked to a rapidly growing literature using mobile phone geolocation data to assess the spread of COVID-19. Most closely related is work by Chiou and Tucker (2020), which finds shelter-in-place effects vary by income. This paper differs by considering the role of leaving the city, connecting mobility with actual COVID exposure, and incorporating analysis of other demographic groups. Other work (Allcott, Boxell, Conway, Gentzkow, Thaler, and Yang, 2020; Barrios and Hochberg, 2020; Engle, Stromme, and Zhou, 2020; Painter and Qiu, 2020; Andersen, 2020) has looked at political partisanship and COVID-19 responses. Prior work, such as Athey, Ferguson, Gentzkow, and Schmidt (2019), Chen, Haggag, Pope, and Rohla (2019), and Chen and Rohla (2018), has used mobile phone geolocation data to examine segregation, racial disparities in voting waiting times, and partisanship.

II Data and Specification

II.A *Data*

Mobile location data was sourced from VenPath—a holistic global provider of compliant smartphone data. We obtain unique data on smart phone GPS signals. Our data provider aggregates information from approximately 120 million smart phone users across the United States. GPS data were combined across applications for a given user to produce pings corresponding to time stamp-location pairs. Ping data include both background pings (location data provided while the application is running in the background) and foreground pings (activated while users are actively using the application). Our sample period covers the period February 1–April 1, 2020.

We connect this data with ZIP-level COVID-19 infection data for New York City,[2] IRS SOI Tax Statistics Data to provide ZIP-level income,[3] and Census ACS data to obtain demographics. We also use county-level Facebook data as discussed in Bailey, Cao, Kuchler, Stroebel, and Wong (2018) and applied in reference to COVID-19 in Kuchler, Russel, and Stroebel (2020).

II.B *Specification*

To isolate the mobility behavior of New York City residents, we employ multiple screens to filter out commuters and visitors, and then assign New York City residents a "home

[2] Available at `https://github.com/nychealth/coronavirus-data`

[3] Available at `https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi`

tract:" the Census tract they spend the most time in during night hours. The first filter separates those who spend the night in New York City from those who commute into New York City. We select from the anonymous users those who have the majority of their pings between 6pm and 8am in New York City on at least 3 different days in February, as opposed to any non-New York City county in the US. The second screen enforces a minimum required data density, and keeps only those with at least 3 pings on at least 5 days in the data in New York City during night hours, and the same requirements during work hours. The data are joined to Census tracts from New York City Open Data to identify the "home tract" for each user. For each of these users, we find their modal tract during night hours, if it has at least 2 pings. We assign them a home tract if they have a tract that is their modal tract on at least 5 nights of data, resulting in our population of 372,787 unique users for our base analysis.

II.C Leaving the City

II.C.1 Where New York City Residents Go

For identified New York City residents in our sample, we find their modal county each night of the data in March. For each county, we count the number of unique users in the last week of March who were not there in the first week of March, as the number of New York City residents moving to that county. We link this to Facebook's social connectedness data at the county level to connect these moves against pre-existing social networks. We define social connections, as in Kuchler, Russel, and Stroebel (2020), between counties i and j as:

$$SocialConnectedness_{ij} = \frac{FB\_Connections_{ij}}{FB\_Users_i \times FB\_Users_j} \tag{1}$$

II.C.2 Who Leaves New York City

For each user in our sample population of New York City residents, we identify a modal county in the US each night of data. We aggregate based on the home tracts of our sample population. For each home tract on each day, we observe the fraction of the tract's residents who spend the night in a New York City county. We examine the fraction that has left the city at the tract level with respect to income, race, education, and age (from the Census ACS data). We look at the difference in this fraction at the start of March and the end of March to see the fraction of residents leaving.[4]

II.D Adherence to Shelter-in-Place

We examine the population at the home tract-level and then aggregate to the home ZIP-level. We flag each ping for each user if it occurs within their home tract. For each home tract each hour, we take the average of this flag to get the fraction of pings by residents of that tract that occur within the tract. This is our "activity" measure. If it is 0, then all pings by people who have homes in that tract are outside of the tract for that hour. If it is 1, then everyone who lives in that tract is at home.

We exclude tract-hours that do not have 10 unique users pinging. We also exclude tracts with population (from the Census) less than 1000. We exclude entirely tracts that intersect with highways, bridges, and tunnels, because the pings in those tracts are heavily influenced by commuters (geographic data of the bridges, highways, and tunnels comes from New York City Open Data). We also trim the tracts that have the top 5%-ile of data/population because some tracts have much more data than others, and appear to be contaminated by commuters as well. Tracts with median income of 0 are excluded as well. These tracts are aggregated to the ZIP-level. ZIPs with less than 60,000 people are excluded from the analysis. We show time of day response across the last period of our sample, from March 23–April 1.

[4]For this reason, we can observe negative moves from a particular tract.

II.E Impact on Mortality

To examine the impact of mobility on mortality, we link our ZIP-level activity and fraction leaving New York City variables to ZIP-level COVID-19 case data, as of April 15, 2020.

III Results

III.A Leaving the City

In Figure II, we show responses of individuals in leaving New York City by tract. We observe stark patterns in the response of individuals along this extensive margin: residents of Manhattan are substantially more likely to leave the city after the crisis, as are other wealthy parts of the city in Brooklyn. By contrast, residents in Queens—the epicenter of the COVID-19 pandemic in New York City—Brooklyn, and the Bronx are overwhelmingly more likely to stay in the city.

We confirm the role of income as a factor in explaining moves away from the city in Figure III, which shows a heatmap of responses by tract and date. Each observation reflects the fraction of individuals who have left that tract away from New York City, as of each day in our sample. Panel A of this figure shows the responses for all tracts, while Panel B shows the responses in tracts with median household incomes in excess of $100k. We find a large breakpoint in our sample in March 14, as reflected in the sharp changes in colors beginning on that date in a number of tracts, corresponding to a sharp rise in the increase of former New York City inhabitants leaving the city. This break comes just before Mayor Bill Di Blasio ordered schools, restaurants, bars, cafes, entertainment venues, and gyms in the city closed on March 16.[5]

These shifts in leaving the city, however, are concentrated in the higher-income Census tracts, suggesting that richer New York City residents were disproportionately able to

[5] See https://www1.nyc.gov/assets/home/downloads/pdf/executive-orders/2020/eeo-100.pdf.

take advantage of the option to flee the city and escape physical COVID-19 exposure in the city. These results are confirmed in Figure IV, which shows that the propensity to leave the city is strongly increasing in local income, and decreasing in the fraction of the tract that is African-American and under 30. These results are large in magnitude and statistically significant—moving from a tract at the bottom quartile of income to the top quartile raises the fraction of New York City residents who leave by about 3 percent, or about the same as the unconditional average of the number of New York City residents who leave.

Consistent with the idea that departing New York City residents are sheltering with friends, family, or in second homes, Figure V finds a strong link between the locations that New York City residents leave to and their pre-existing social connections. Panel A of this Figure plots the number of out-of-town New York City residents sheltering across American Counties. Panel B of this Figure shows a binscatter plot of the log of social connections between New York City and the county that residents exit to, against the number of New York City residents who exit to that county, as a fraction of the county's residents. The strong relationship suggests that New York City residents with the ability to leave generally went to areas where they had pre-existing social networks, and could take refuge with friends and family. This finding also potentially helps to explain the result in Kuchler, Russel, and Stroebel (2020), that greater social connections with Westchester (another pandemic hub) helps to predict subsequent COVID-19 deaths. A plausible transmission mechanism is the refugee behavior of New York City residents into these socially connected regions, which has been frequently cited by local officials as a possible transmission mechanism of the disease.[6] This relationship is robust to controls for physical distance between New York and other counties, pointing to social connections specifically as a key driver of exit destination choices.

[6]For instance, the Governor of Rhode Island mandated a 14-day quarantine for New York City residents entering the state, punishable with a fine or arrest, see https://www.nytimes.com/2020/03/28/us/coronavirus-rhode-island-checkpoint.html. Preliminary results suggest that counties with greater New York evacuees do have more COVID-19 cases.

III.B Adherence to Shelter-in-Place

We also examine the mobility responses of residents who stay, and also find strong differences in responses across demographic groups. In Figure VI, we show a heatmap of mobility responses by hour of day across tracts ordered by different demographic groups, over the last portion of our sample from March 23–April 1. We calculate the average number of residents whose ping data indicates that their physical activity resides in their home tract, instead of another portion of the city. This measure is intended quantify the amount of sheltering at home taking place at the tract-level.[7]

Panel A shows mobility responses ordered by tract-income. A darker green color indicates that individuals, in that tract and hour of day, were more likely to stay in their home tract, instead of being observed in a different tract in the city. We find darker green colors in the bottom of the plot across times of day, corresponding to the higher-income tracts. These results suggest that richer areas were able to shelter more effectively—both during normal work hours, as well as in after work hours. We find evidence that areas that are more black shelter less (Panel B), as well as areas that are more Hispanic in Panel A of Figure VII, and areas that are less educated in Panel B of Figure VII.

We examine sheltering responses during daytime hours in Figure VIII, and find that lower-income, Hispanic, and African-American areas show more out-of-tract activity during these ties. These results are consistent with Almagro and Orane-Hutchinson (2020), suggesting that since minority and lower-income workers are more likely to be front-line employees, they are more likely to be working out of the home during those hours. However, we also find that individuals are more likely to be out of tract during nighttime hours as well, in Figure IX. These results suggest that these populations are less likely to adhere to strict shelter-in-place measures. We speculate that this may be due to the need

[7]We use the home tract, rather than the precise building, to incorporate possible measurement error in ping locations. As a result, we may misclassify short trips outside the home, but within the tract, as representing stay at home behavior.

for more frequent retail visits, for instance, while delivery options for groceries and food may be more common in more affluent areas. An alternative possibility is that these populations may be forced to work additional hours as essential personnel. Future work will explore the nature of these responses.

Overall, our findings indicate that more vulnerable populations exhibit greater mobility patterns out of the home, increasing their likelihood of exposure to COVID-19.

III.C Impact on Mortality

In Figure X, we return to our motivating Figure I on COVID-19 exposure by different demographic groups.[8] We now compare the impact of different tracts on cases, after controlling for two mobility indicators: the number of individuals leaving the city, as well as the mobility of individuals in the city. We plot the residuals from a regression of caseload per capita on those two mobility regressions (adding back the constant). Panels A and B suggest a much more flat relationship—suggesting that differential exposure through mobility may explain much of the apparent relationship between demographic variables and COVID-19 exposure. In additional regressions, available upon request, we find that the magnitude and statistical significance of demographic factors disappears after inclusion of local mobility factors.

We caution that it is unlikely that mobility, alone, explains the full nature of COVID-19 sensitivity. In particular, the severity of the disease for different demographic groups may be very different, reflecting other health disparities in comorbidities such as diabetes. We continue to find a more positive relationship in Panel C, examining Hispanic areas, suggesting that these populations may have additional mobility risk factors other than the ones examined here. While these results are not fully conclusive, these correlations provide important suggestive evidence that mobility factors may drive a portion of

[8]While the number of cases per capita may reflect testing bias, in Appendix Figure XI we examine the fraction of test results which come back positive. We find even higher positive test results as a fraction in lower-income, higher African-American, and higher Hispanic areas. These results may suggest that, if anything, vulnerable population cases are undercounted.

the relationship between COVID-19 caseload and demographic factors, to be pursued in future research.

IV Conclusion

Even in a dense urban hotspot for coronavirus, we find important spatial inequities in mobility that have consequences for racial and income disparities. Richer New York City residents are able to take advantage of the insurance provided by social capital and the availability of housing outside of the city to leave the epicenter of the pandemic. We document a substantial increase in out-of-town exits in higher-income parts of New York City, destined for areas with high social connections to New York CIty. Among residents who stay, we also find disparities in movement both during typical work hours as well as in the night-time. Lower-income areas, regions with higher Hispanic and black populations exhibit greater out-of-tract mobility during both work hours as well as during the nighttime. These mobility patterns are consistent with lower-income and minority populations being more likely to occupy frontline occupation roles and make more frequent retail visits, potentially increasing their exposure to COVID-19. Controlling for these mobility patterns greatly lowers the apparent contribution of these demographic factors on COVID-19 caseload.

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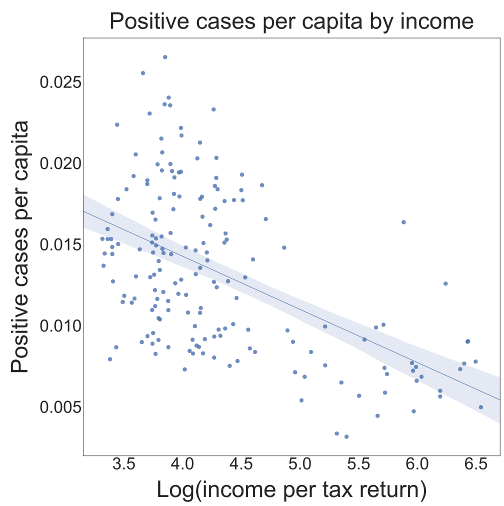
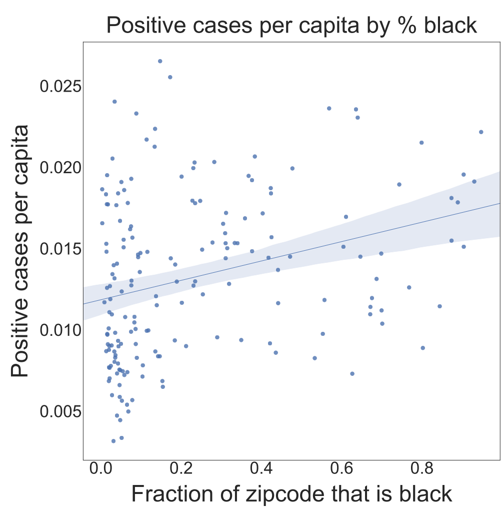
FIGURE I: COVID-19 Cases in NYC by Demographics

Panel A: COVID-19 Cases by ZIP Income



Panel B: COVID-19 Cases by ZIP by Fraction African-American



Panel C: COVID-19 Cases by ZIP by Fraction Hispanic

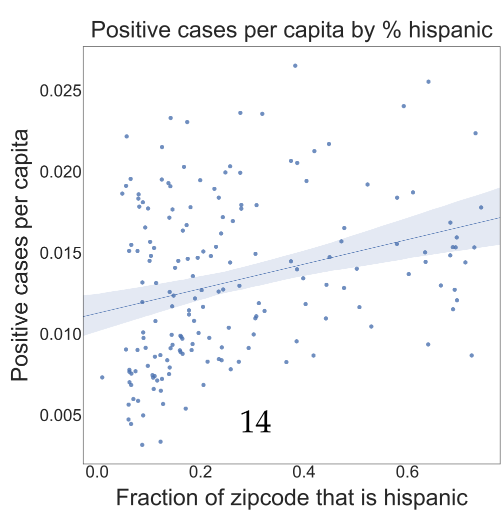


FIGURE II: Propensity to Leave NYC by Tract

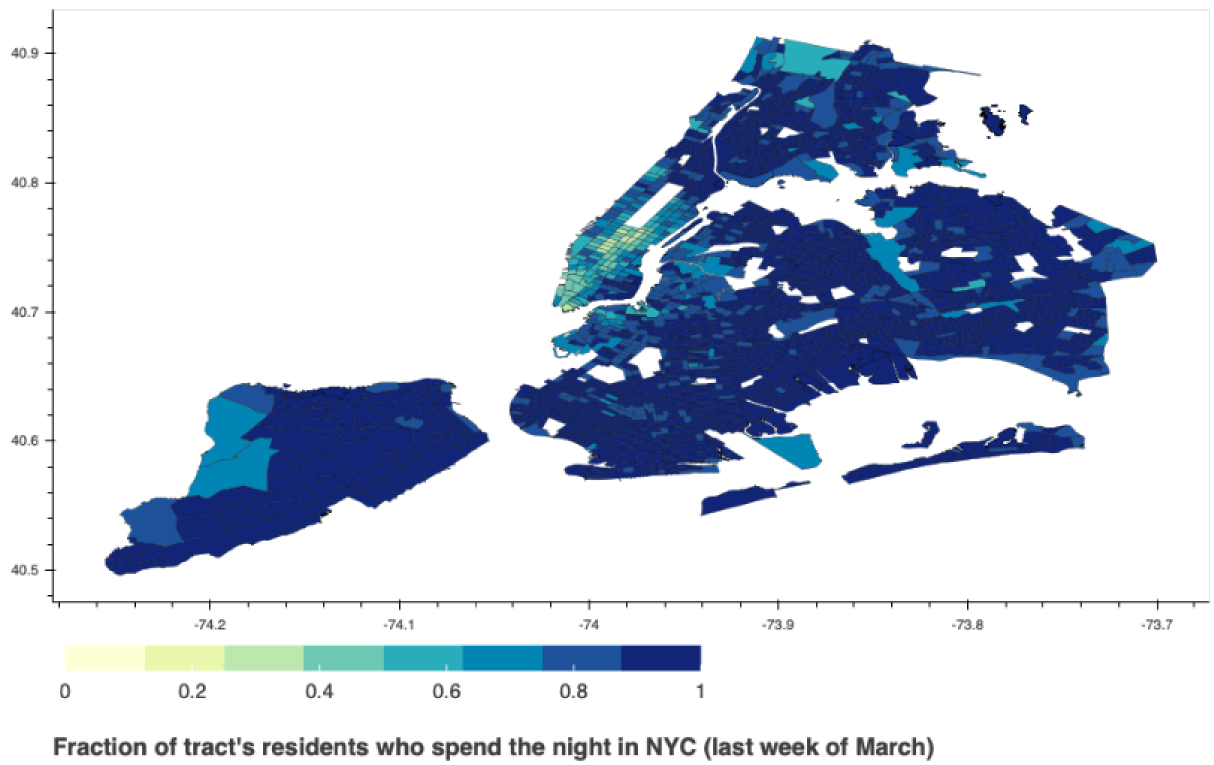
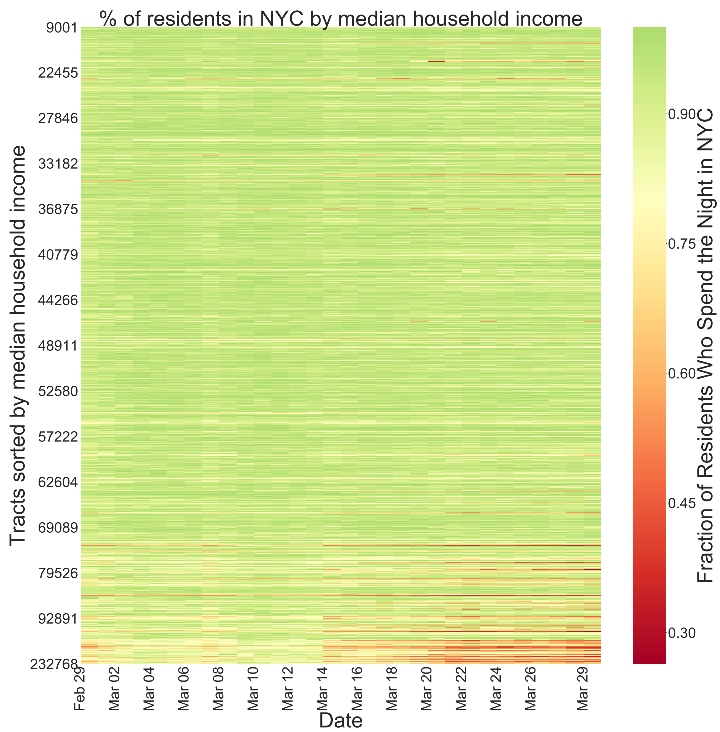


FIGURE III: Propensity to Leave NYC by ZIP Income

Panel A: Heatmap of Tract Propensity to Leave NYC by Date



Panel B: Heatmap of Tract Propensity to Leave NYC by Date, \$100k > tracts

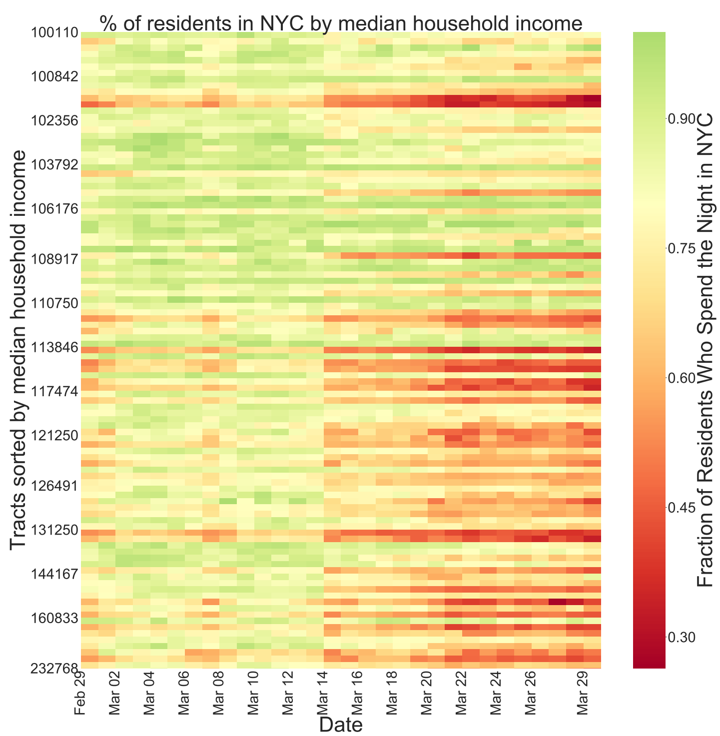
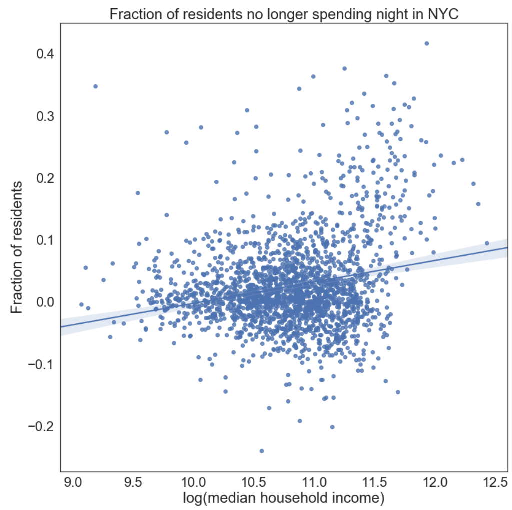
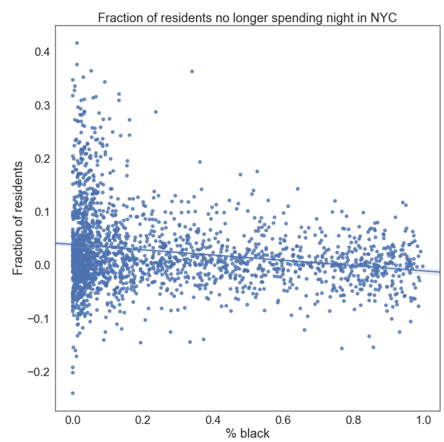


FIGURE IV: Fraction Change in Out of Town Visits by Demographics

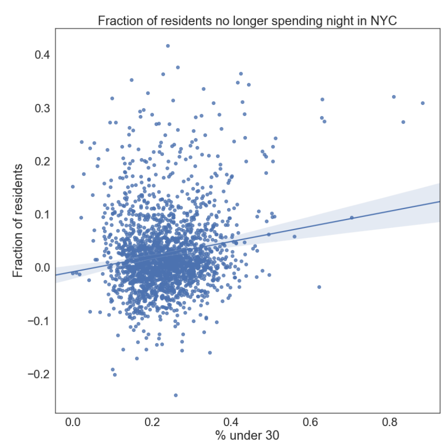
Panel A: Change in Out of Town Visits by ZIP Income



Panel B: Change in Out of Town Visits by Fraction African-American



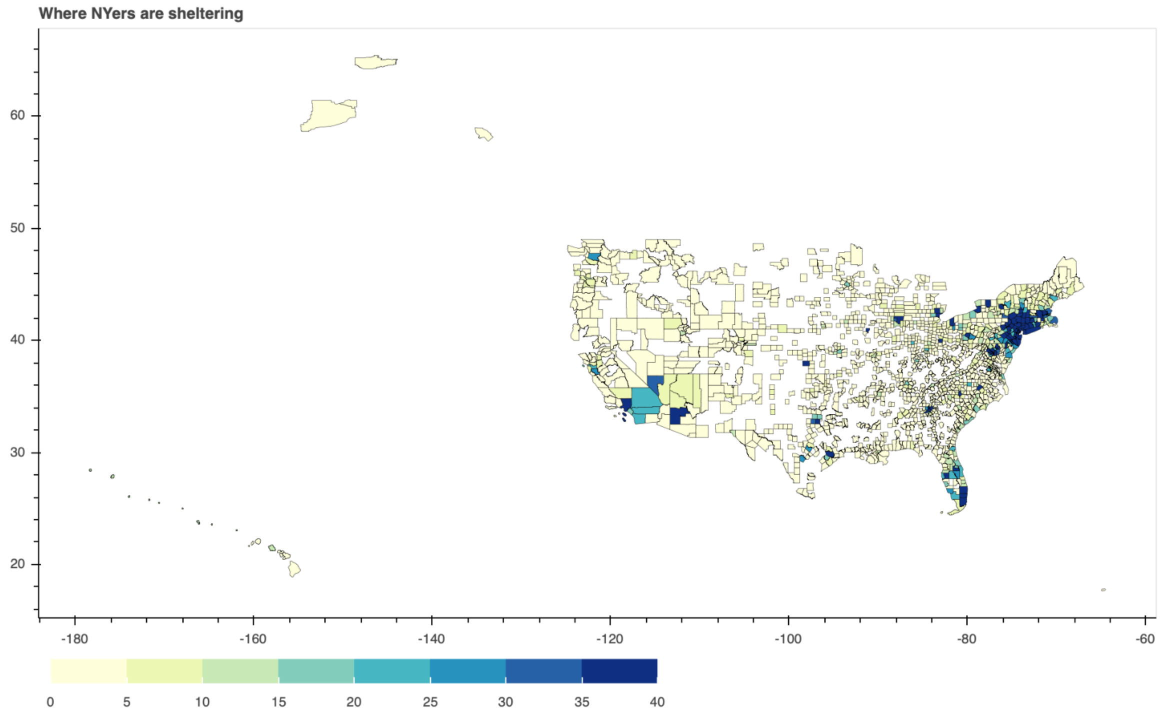
Panel C: Change in Out of Town Visits by Fraction Under 30



Notes: Panel A shows the average income of ZIPs against the fraction of people in each ZIP who test positive for COVID-19. Panel B repeats the exercise for the fraction who are black, and Panel C for the fraction that is under 30. COVID-19 case data are drawn from https://github.com/nychealth/coronavirus-data, income data is drawn from the IRS SOI Tax Statistics at https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi, and demographic data are drawn from the ACS.

FIGURE V: Propensity to Leave NYC by ZIP Income

Panel A: Counties with Presence of Individuals Departed from NYC



Panel B: County NYC Residents against Social Connections with NYC

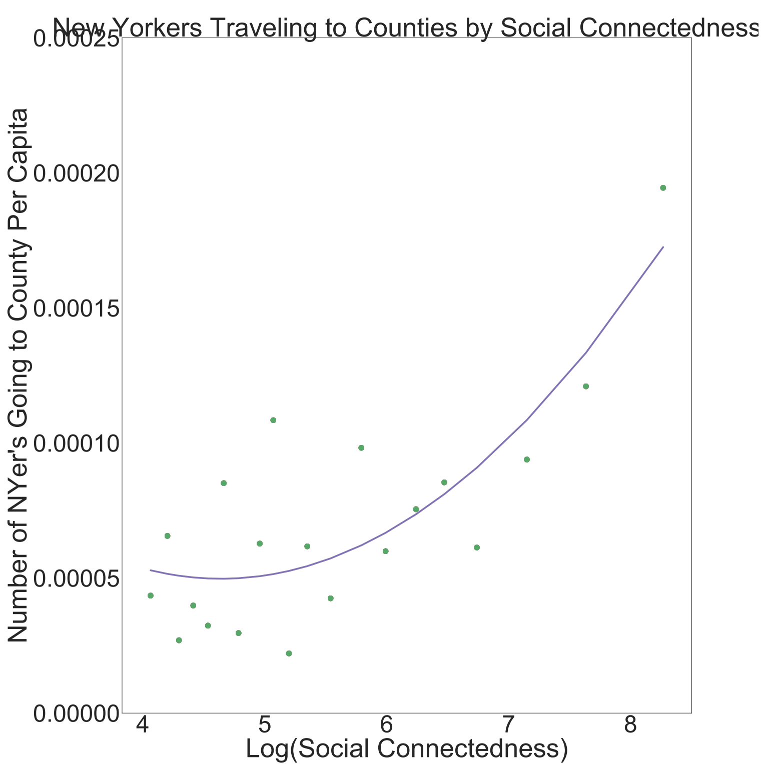
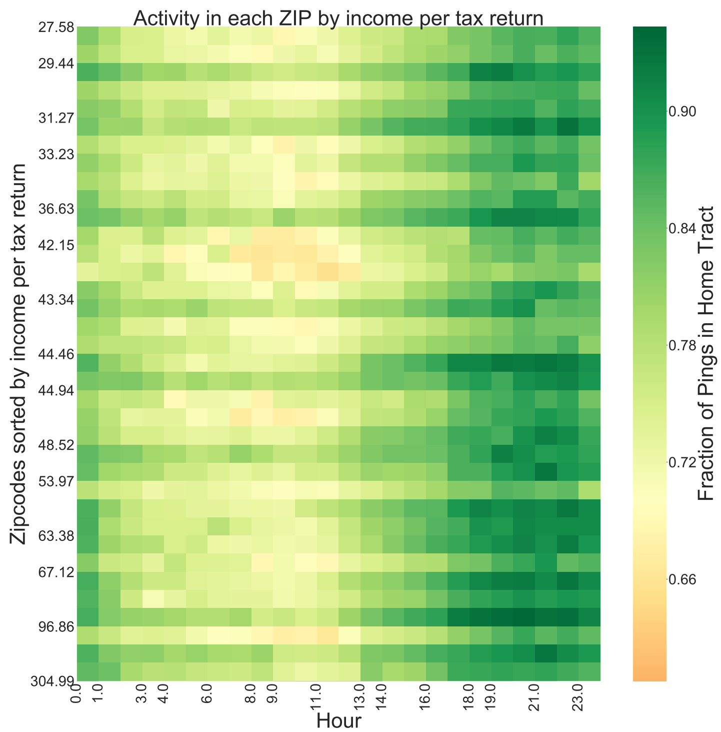


FIGURE VI: Time of Day Activity by Demographics—Income and Fraction African-American

Panel A: Time of Day Mobility by ZIP Income



Panel B: Time of Day Mobility by Fraction African-American

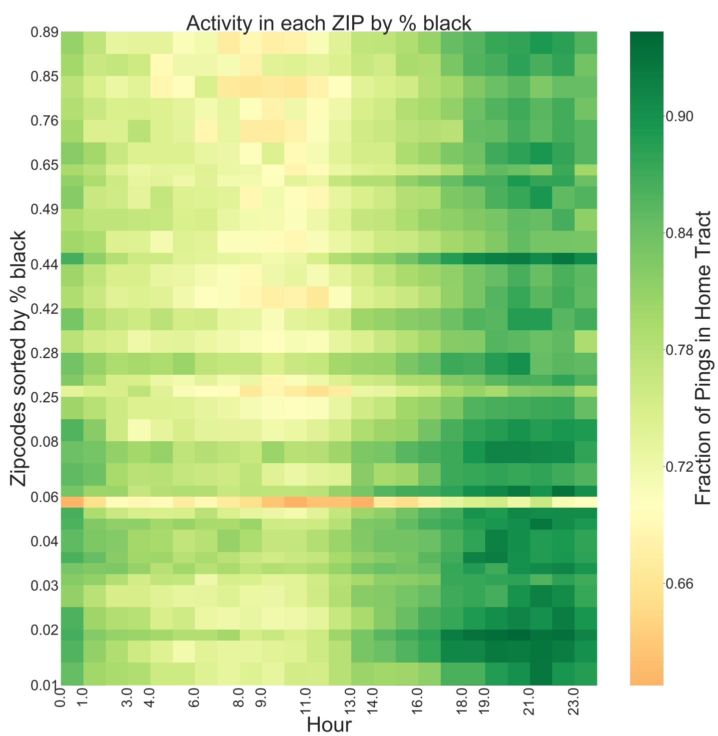
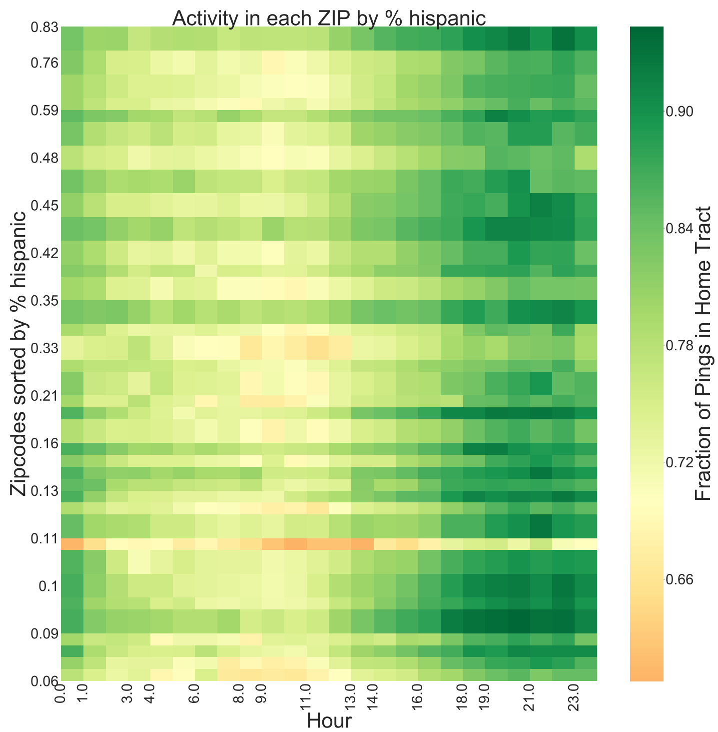


FIGURE VII: Time of Day Activity—Hispanic and Education Share

Panel A: Time of Day by Fraction HIspanic



Panel B: Time of Day by Fraction less than College Educated

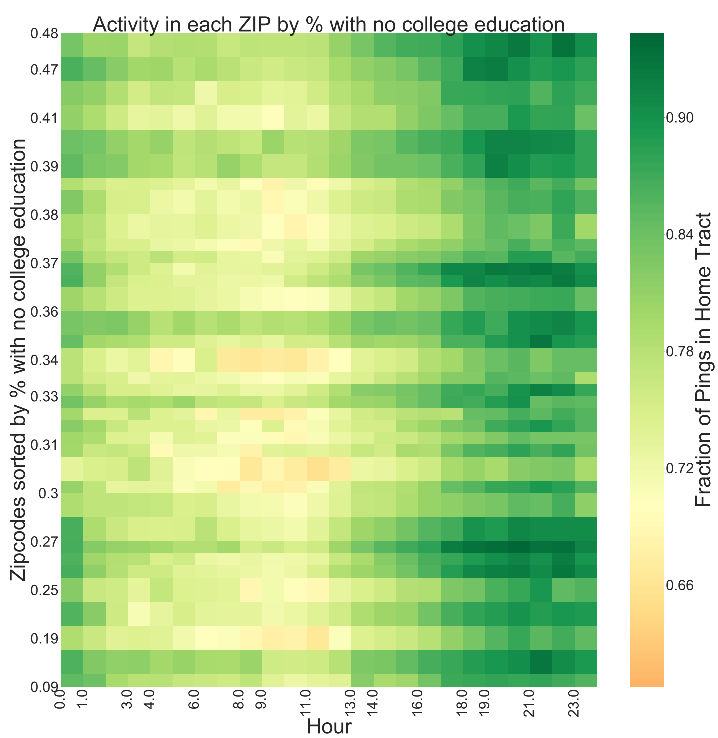
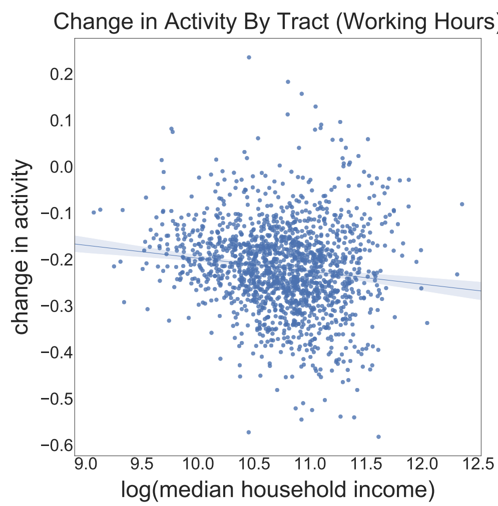
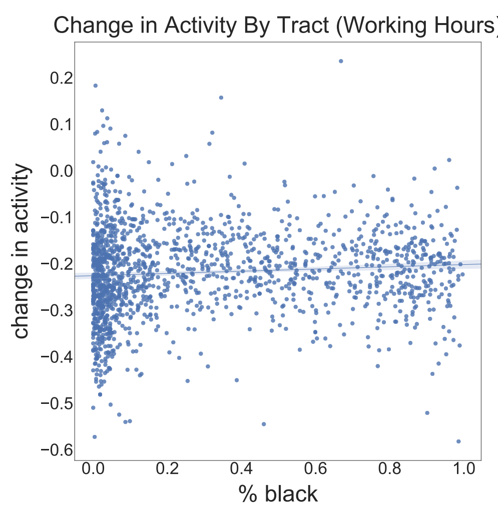


FIGURE VIII: COVID-19 Cases in NYC by Demographics

Panel A: COVID-19 Cases by ZIP Income



Panel B: COVID-19 Cases by ZIP Fraction Black



Panel C: COVID-19 Cases by ZIP Fraction Hispanic

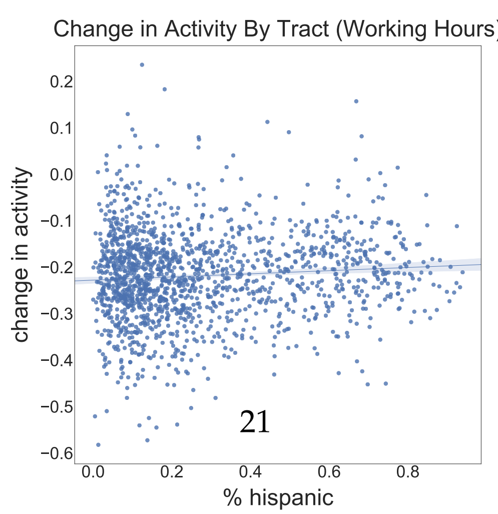
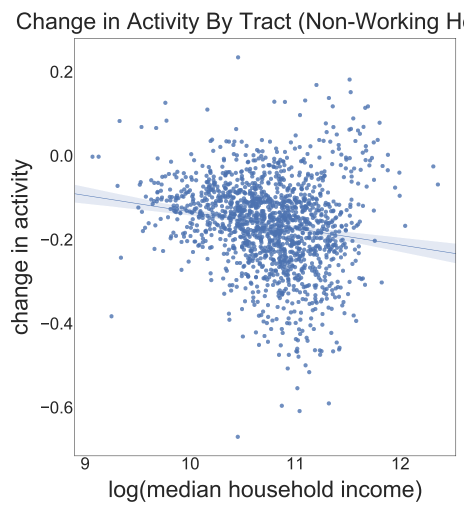
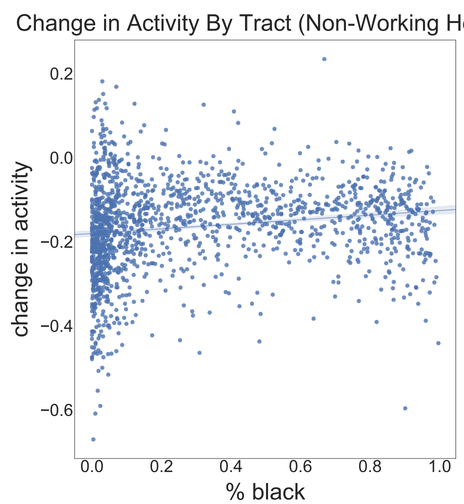


FIGURE IX: COVID-19 Cases in NYC by Demographics

Panel A: COVID-19 Cases by ZIP Income



Panel B: COVID-19 Cases by ZIP Fraction Black



Panel C: COVID-19 Cases by ZIP Fraction Hispanic

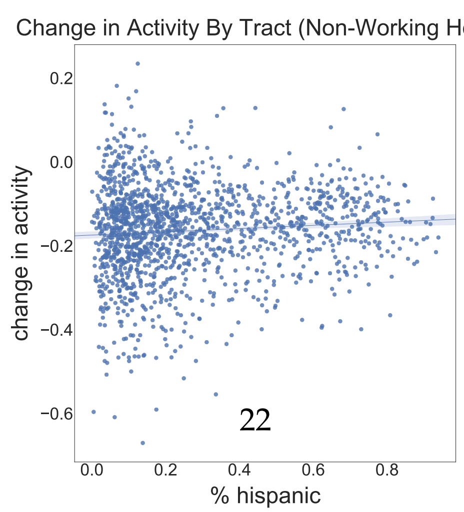
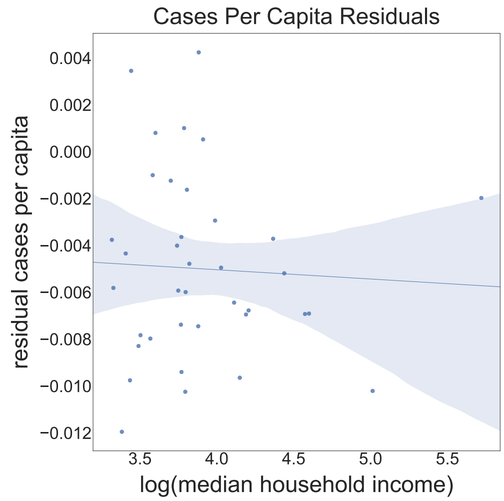
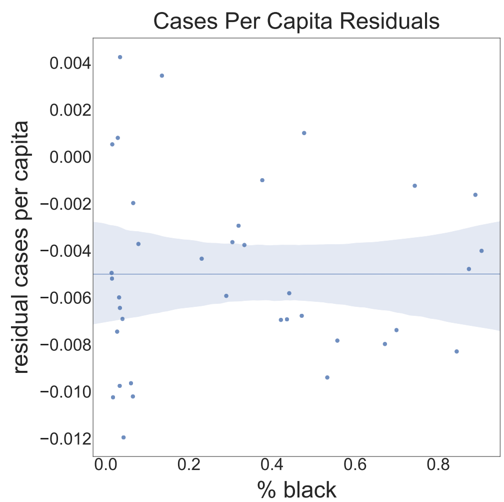


FIGURE X: Residual Effect of ZIP after Controlling for Mobility

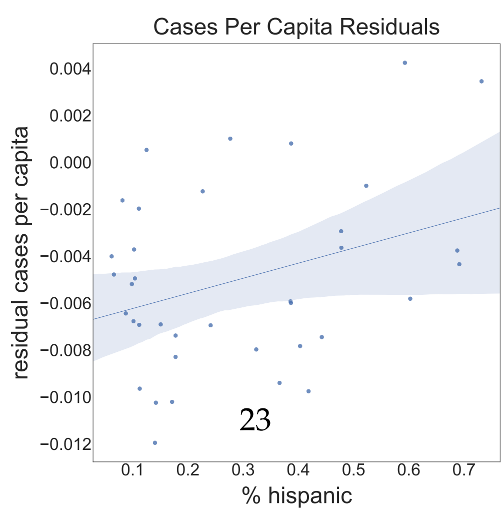
Panel A: Residualized COVID-19 Cases by ZIP Income



Panel B: Residualized COVID-19 Cases by ZIP Fraction African-American



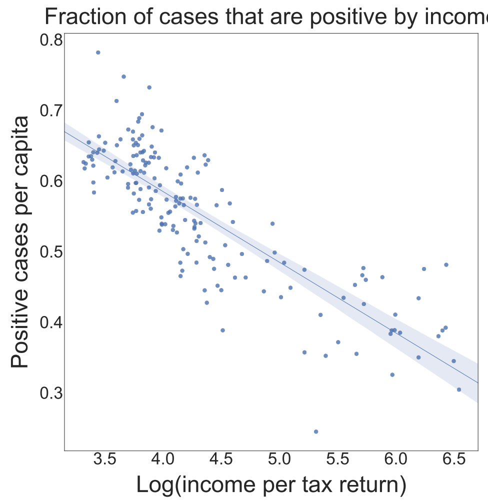
Panel C: Residualized COVID-19 Cases by ZIP Fraction Hispanic



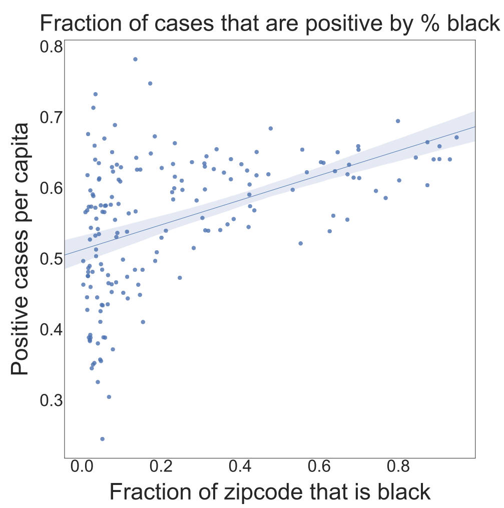
A Appendix

FIGURE XI: Fraction of COVID-19 Test Results Positive by Demographics

Panel A: Fraction of COVID-19 Test Results Positive, by ZIP Income



Panel B: Fraction of COVID-19 Test Results Positive, Black



Panel C: Fraction of COVID-19 Test Results Positive, Hispanic