Businesses in high-income zip codes saw sharper foot-traffic reductions during the COVID-19 pandemic

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Abstract

As the COVID-19 pandemic unfolded, the mobility patterns of people worldwide changed drastically. While travel time, the cost of the service, and trip convenience had always influenced mobility, the risk of infection and policy action such as lockdowns and stay-at-home orders emerged as new factors to consider in the mobility calculus. Using SafeGraph mobility data from Minnesota, USA, we demonstrate that businesses and point-of-interest locations in the more affluent zip codes witnessed much sharper reductions in foot traffic than their poorer counterparts. We contend post-pandemic recovery efforts should prioritize relief funding accordingly.

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Introduction

The urban landscape, a vital engine of social and economic opportunity, is a daily witness to intense face-to-face socioeconomic interactions that exhibit an excellent regularity. In the absence of restrictions on spatial mobility, residents of a city typically have plans for times within the day that they wish to stay indoors vs. outdoors or which businesses or locations to visit. However, the same people are forced to re-optimize once constraints are externally imposed due to a disease-related lockdown. Depending on the timing and nature of the restrictions, some residents a) cut down most travel outdoors and hunker down at home, b) reduce mainly non-essential or easily substitutable travel, and c) switch to other businesses and locations different from ones they would patronize pre-lockdown. Businesses, especially those relying on face-to-face transactions, see the effects of changes in the mobility calculus on the foot traffic they see.

In March 2020, the transmission of the Sars-Cov2 virus had reached pandemic proportions, and governments worldwide were scrambling to formulate a policy response. Wherever possible, governments enacted aggressive policies, including “shelter in place” and emergency closures of all non-essential services, with associated economic and social consequences. In Minnesota, USA, the first stay-at-home order was imposed on March 16, 2020. It forced many Minnesotans to remain home most of the time and re-optimize their daily outdoor-indoor mobility calculus. Some had to cut down on restaurant visits, others on trips to the gym, movie theaters, doctor offices, pharmacies, or grocery stores. How did the vastly altered mobility landscape affect businesses and point-of-interest locations? Did location matter: did companies located in high-income zip codes see sharper declines in foot traffic than their counterparts in others? This paper documents pandemic-influenced foot-traffic patterns to businesses in Minnesota’s high- and low-income zip codes following the onset of COVID-19.

The research is framed as follows. Consider a particular outdoor activity, call it X, and suppose pre-lockdown, residents of poor and rich urban areas engage in X, possibly at different scales. For concreteness, say X is restaurant visits and before the lockdown, the poor area “consumed” $X_p$ and the rich “consumed” $X_r$, where $X_r > X_p$. Suppose, post lockdown, both $X_p$ & $X_r$ fell. We ask, which fell more? And for how long? Which recovered (to pre-lockdown levels) faster? Are the patterns similar across other activities such as Y and Z? For example, did people in wealthy areas curtail restaurant or gym visits while those in poor neighborhoods missed doctors’ visits or pharmacy trips?

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1 Bundorf et al. (2021) present evidence of large activity reductions in the presence of lockdowns in the U.S.: “40 percent of people reported reducing their activity by a lot for grocery shopping, while 79 percent of people reported reducing their activity by a lot for restaurant visits, consistent with grocery shopping being a more essential activity.” Galeazzi et al. (2021) find for France, Italy and UK, lockdowns create “smallworldness —i.e., a substantial reduction of long-range connections in favor of local paths.” Cronin and Evans (2020) study foot traffic data for the US and find self-regulating behavior on the part of customers resulting from the changed calculus explains more than three-quarters of the decline in foot traffic in most industries; restrictive regulation explains half the decline.

2 Apedo-Amah et al. (2020) document the severe, widespread, and persistent negative impact on sales across firms worldwide.
To place our research questions in context, consider Figure 1, which compares the mobility surrounding restaurants within two cities in Minnesota with vastly different median incomes: Prior Lake has a median household income of $109,609, more than double Hibbing’s income of $49,009. The vertical axis measures restaurant visits during 2020-21 as a fraction of the same for 2019. (The data sources are described further below.)

As 2020 starts, it is apparent that both the yellow (Prior Lake) and the blue (Hibbing) lines are similar through January and February, with the yellow being above the blue. However, soon after the first lockdown period started in March 2020, both lines began to show steep declines. (Note that the shaded regions represent indoor dining venues’ lockdown periods.) Once restaurants reopened in June 2020, differences between the two come into sharp focus: Hibbing’s restaurant visits recover to near pre-pandemic levels, while those in Prior Lake restaurants only achieve a sluggish recovery and remain at depressed levels for months after. Prior Lake’s restaurants show a significant spike in visits during the second lockdown. In contrast, Hibbing’s restaurants slowly lose visitors, possibly due to more curbside pickups by Prior Lake’s residents for Thanksgiving.

Our primary contributions are as follows:

- We outline a pairwise comparison method that compares the reduction in visits to businesses in two groups of zip codes (top and bottom one-third of zip codes by median income). This method accounts for differences in individual zip code population sizes and calibrates it to the usual number of visits to each business location based on past years.

- The main table shows for 22 different North American Industry Classification System (NAICS) business categories whether businesses in wealthier zip codes had a more significant decrease in visits than businesses in poorer zip codes. These metrics are calculated for periods in different stages of the pandemic.
This paper contains kernel density estimation plots of all possible pairwise comparisons of changes in visits for select business categories to show the dispersion of comparisons during different periods.

The answers could be of great value to policymakers trying to design a lockdown to reduce disease spread with minimal disruption to people’s lives and business operations. The knowledge that businesses in rich and poor urban areas withstand mobility shocks differently can help decide which companies and locations to place under the lockdown and which ones to spare. Our research can also guide where scarce relief dollars should go. For example, suppose movie theaters are visited mainly by the affluent who sharply curtail theater visits (but not gym visits) post lockdown. In that case, it could be argued relief dollars should go to theater owners before going to gym owners. Our research is not intended to shed light on the sort of measures required to contain the spread of the disease; it takes the disease, its progression, and the policies as given and attempts to understand their effect on commerce.

Our paper is in line with recent literature analyzing mobility differences in the US which finds that high-income neighborhoods increased days at home substantially more than low-income neighborhoods. Some of this is explained by the enhanced capacity of the rich to work from home. Another angle that may explain the difference in stay-at-home days is risk perception.

1. Data
   i. Mobility Pattern

We use data from the SafeGraph COVID-19 Data Consortium to observe human mobility patterns. SafeGraph collects GPS information from about forty-five million anonymized smartphones devices and 3.6 million point-of-interest (POI) locations in the US. The GPS data comes from apps where users have consented to location tracking. Within the SafeGraph COVID-19 Data Consortium, there are three primary datasets, of which we use two: Weekly Patterns and Core Places. From the Weekly Patterns dataset, we use data on the number of visits each week to each POI (foot traffic) in the area we are analyzing. SafeGraph counts a visit to the POI by checking if the GPS location matches the inner boundary of a POI location. We use the Core Places dataset to bring additional information on each POI, such as the North American Industry Classification System (NAICS) code, street address, city, region, and zip code. We merge both datasets by matching the unique POI identifiers “safegraph_id” (to separate POIs of the same name but different locations) to create a single dataset with millions of records. Each record contains the POI name, the two dates marking the beginning and end of a specific week, the number of visits in that week, the POI’s city, the POI’s zip code, the POI’s NAICS code, and the POI’s “safegraph_id.”

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\[d\] Although device-level demographic data cannot be collected, SafeGraph estimates which census block group the device owner’s home belongs to. The data is well-sampled across household income averages, educational attainment, and demographic categories, according to the aggregate summary of SafeGraph data and the characteristics Census block group.

\[e\] The mode of travel is not recorded in SafeGraph data, only the number of visits to the POI. This study is interested in how visitors to businesses are changing, and foot traffic refers to the number of visits to businesses.
ii. Income and population

Income and population data comes from 2015-2019 American Community Survey 5-year Estimates\(^\text{10}\). The zip code is our geographic unit in this study. To divide rich and poor areas, we rank zip codes by the median income of residents; the top one-third are classified as high-income and the bottom one-third as low-income.

2. Methodology

We choose to analyze the difference in mobility patterns to Minnesota’s businesses because of the range of clearly articulated policies employed during various pandemic stages.

The first stage is the pre-pandemic baseline, from February 2, 2020, to March 16, 2020; the second is the first lockdown, March 17, 2020, to June 1, 2020; the third is the interim when businesses reopened, June 2, 2020, to November 23, 2020. The next period is the second lockdown, November 24, 2020, to January 11, 2021, and the last period is the reopening period from January 11, 2021, to May 31, 2021. These dates line up with the initial plans for reopening Minnesota.

Our geographical unit is the zip code, denoted by \( j \). Let \( i \) represent the business category (e.g., full-time restaurants), \( k \), the number of businesses under category \( i \), and \( t \) the time period mentioned above. Let \( v \) denote visits, our measure of mobility\(^1\). First, we compute the number of visits to a given business in a zip code, \( v_{ijt} \). Next, we compute \( V_{ij} \equiv \sum_k v_{ijt} \), the sum of visits to every business in category \( i \) in zip code \( j \). Then, we compare \( V_{ij} \) versus the number of visits to the corresponding weeks in the year 2019, denoted by \( V_{ij,pre} \). Comparing the number of visits in 2019, we can account for normal variations such as holidays or seasonality. In addition, it removes the tracking bias that is consistent across 2019-2021 in the same area.

Table 1 shows the corresponding period dates in 2020-2021 to the dates in 2019.

|                | Year 2019          | Year 2020-2021     |
|----------------|-------------------|--------------------|
| Normal         | 2/04/19 - 3/18/19 | 2/03/20 - 3/16/20  |
| Lockdown 1     | 3/18/19 - 6/03/19 | 3/16/20 - 6/01/20  |
| Reopening 1    | 6/03/19 - 11/25/19| 6/01/20 - 11/23/20 |
| Lockdown 2     | 11/25/19 - 20 - 1/14/19| 1/23/20 - 1/11/21 |
| Reopening 2    | 1/13/19 - 6/01/19 | 1/11/21 - 5/31/21  |

Our identifying assumption is, had the pandemic not happened, \( V_{ijt} \) would be very similar to the same time period in 2019, \( V_{ij,pre} \). This assumption allows us to ascribe changes in visits to the lockdown, the

\(^{1}\) The number of visits is a good indicator of economic activity. We are unable to estimate the change in spending due to a lack of data.

\(^{2}\) We look at the number of visits by duration and find that visits of less than 5 minutes, which include pick-up and delivery orders, did not increase significantly during the lockdown. Unfortunately, we are unable to distinguish between delivery orders and pick-up orders, as a single driver can pick up multiple delivery orders. The change is plotted in the appendix figure.
fear of the virus, or both. We divide the number of visits by the zip code population to make the change
in visits comparable across zip codes.

In our sample, \( j = \{1,2,\ldots,574\}, j \in H \cup L \) where 287 zip codes are classified as low-income (denoted \( L \)) and the rest are high-income (denoted \( H \)). Next, we compare all possible (82,369 combinations) pairwise

differences in the change in the number of visits for high- and low-income zip codes. That is, we take one

high-income zip code and compare its population-deflated

\[ \Delta_{ij} = (V_{ij} - V_{ij\text{pre}}) \]

with the same for a

low-income zip code

\[ \Delta_{ij} = (V_{ij} - V_{ij\text{pre}}) \]

We do this for all possible pairwise combinations for all \( j \).

\[ (V_{ilt} - V_{ilt\text{pre}}) - (V_{ilt} - V_{ilt\text{pre}}) \]

for all \( h \in H \) and \( l \in L \).

If this number is negative, it follows that the high-income zip codes saw a greater reduction in visits during

period \( t \) to business \( i \) compared the low-income zip code.

Finally, we construct the distribution of all differences across all possible combinations. We produced such
distributions for \( \{1,2,\ldots,21\} \) different business categories and \( \{1,\ldots,5\} \) different periods. The
results are summarized in Table 2

Consider the following simple illustration: imagine two rich areas, \( a \) and \( b \), and two poor areas, \( x \) and \( y \).

For each business type, there are four possible pairwise comparisons. For business type \( i \), the possible

comparisons are \( \Delta_{ia} - \Delta_{ix}, \Delta_{ia} - \Delta_{iy}, \Delta_{ib} - \Delta_{ix}, \Delta_{ib} - \Delta_{iy} \). If \( \Delta_{ia} - \Delta_{ix} < 0 \), this means that visits to

business \( i \) in area \( a \) decreased more than in area \( x \) compared to its visits in 2019. If \( \Delta_{ia} - \Delta_{ix} = 0 \), means

that the change in visits is the same in area \( a \) and \( x \). We obtain the distribution by computing this pairwise

comparison for all possible cases. Distribution centered at zero means that the change in visits in low- and

high-income area is not different.

Results

Figure 2 and Figure 3 plot the kernel density estimation (KDE), a smooth and continuous density

estimation of all possible pairwise comparisons of changes in visits to full-time restaurants and groceries

between low- and high-income zip codes. Each color represents the distribution during the indicated

period. The black plot is the pre-pandemic difference centered at zero for both business locations.

The variance is slight, meaning visits to full-time restaurants or groceries did not differ from the previous

year by location. In other words, low- and high-income areas had a parallel trend in visits in the pre-

pandemic period. The same trend is observable for almost all categories, \( i \). Things changed once the

pandemic got underway. The red line plots the distribution during the first lockdown in March 2020: the

distribution is centered to the left of zero. This means, on average, restaurants in prosperous zip codes

had fewer visitors than businesses located in low-income zip codes. This pattern persists until the last

reopening period starting from 2021. On the other hand, the pattern of visits to groceries and

\( ^{\text{h}}\) We also conducted a sensitivity analysis by changing the thresholds for high- and low-income zip codes from one-third to one-fourth. In that case, only 216 zip codes were reclassified as high-income and 216 as low-income. We

also changed the threshold from one-third to two-fifths, so there were 344 high-income and 344 low-income zip codes. After constructing distributions based on the reclassifications, we found the results were similar to the

baseline one-third threshold, the one we chose to report.
supermarkets in Figure 3 is similar in both zip codes across all periods: the distribution is centered on zero, indicating that both the rich and the poor reduced their visits in much the same way. This means that groceries can be considered essentials. For example, before the pandemic, households did their grocery shopping every three days; after the pandemic, they did it every ten days, but they couldn't go any lower because fresh food would spoil. Furthermore, many items had purchase limits in 2020, restricting the ability to stock up to reduce the number of trips to the grocery store regardless the income level.

Figure 2 Relative changes in the number of visits to full-time restaurants between low- and high-income zip codes

Figure 3 Relative changes in the number of visits to groceries and supermarkets between low- and high-income zip codes
To make the comparison more accessible, we summarize the result of 21 business categories in Table 2. It presents the cumulative distribution that is less than zero. If the number is 50%, the distribution is centered at zero. Higher percentages indicate that the distribution is centered on the left side of zero, implying that high-income zip codes had fewer visitors than low-income zip codes compared to the pre-pandemic times. We colored blocks as dark red if the percentage exceeds 70%, light red for greater than 60% and less than 70%, light blue for greater than 30% less than 40%, and dark blue for less than 30%. Thus, the color blue indicates that poorer zip codes saw a sharper reduction in visits to that type of service than rich zip codes, and the color red, vice versa.

From Table 2, we observe that richer zip code-people reduced their visits to restaurants, religious organizations, and movie theaters. On the other hand, poorer zip code-people reduced their visits to plumbing, heating & AC contractors, veterinary services, funeral homes, polices stations, and libraries. One notable feature of Table 2 is that many blue cells are on the lockdown period, implying poorer zip code-people substantially reduced their mobility during the first lockdown. Another noticeable feature is that more affluent people stopped visiting places known to be prone to infection, suggesting better abilities to comply with the lockdown policy via switching to substitutes. For example, reducing restaurant visits could be because more prosperous people started to use more delivery services. The change in visits to essential services such as supermarkets, gasoline stations, and medical services is similar for rich and poor areas. The number of rich and poor zip codes that had at least one location of a particular business category are listed in the last two columns within the Appendix, Table A1.

A notable fact from Figures 1 and 2 is that dispersion in mobility increased during the pandemic. Compared to the pre-pandemic level, the variance in the difference of the change in visits across rich and poor zip codes increased regardless of the type of business. This is observable even in industries where the distribution of the difference after the lockdown is centered at zero, such as groceries. This means that, on average, the reduction of visits to groceries is similar between the rich and poor areas. Still, people within similar income groups started to exhibit different mobility patterns after the pandemic, which was not observable before. For example, some affluent areas sharply reduced outdoor trips compared to others from similar income areas. Some poor areas maintained a level equivalent to the pre-pandemic level, while others declined to go outside. This implies that other factors than median income may be affecting the rich and poor areas to behave differently. This could be income inequality, the number of jobs that can be done remotely, age composition of the zip code, perception about the epidemic, and so on.

To sum up, before the pandemic, visits to certain businesses were similar regardless of the median income of the zip code – the pre-pandemic distribution of the pairwise comparison is centered at zero. The small variance of the pre-pandemic distribution indicates that the mobility patterns were homogeneous within the income group. However, after the pandemic, rich and poor areas diverged into having different visiting patterns. This is confirmed because the distribution after the pandemic moved in different directions depending on the type of service. Furthermore, higher pairwise distribution variance during the pandemic period suggests that people are diverging from the typical income group pattern after the pandemic. This disparity could be explained by factors other than income.
Conclusion

The COVID-19 pandemic and subsequent restrictions impacted different types of businesses in zip codes with high and low median incomes, as shown above. We show that the effects differed across various business categories in distinct periods. Comparing the number of visits during the pandemic to data from 2019, more than a year before the COVID-19 pandemic hit the US, and adjusting visit totals relative to current population counts in each zip code were factors we used to normalize data into a comparable format. Another metric we gained in our analysis was the distribution of a particular business type between richer zipcodes and poorer zip codes (e.g., number of child care businesses in richer zip codes compared to poorer zip codes). Regardless of how businesses were hit, there was a considerable divergence in mobility between richer and poorer zip codes in most business categories. In addition, within each income group, the mobility of people diverged from the pre-Covid pattern of the group. This research can assist policymakers who are implementing lockdown policies but still want to keep economic disruptions to a minimum. Furthermore, because there was a different pattern of foot traffic changes across zip codes of high and low median income, the results can contribute to the design of post-pandemic recovery programs. Future research could explore into how mobility changed based on various metrics, such as the most common jobs held by people in different zip codes. It could also look at changes in people's spending or business revenue and its associated job losses, to assess the economic impact of the policy. Lastly, there is also potential for different mobility patterns to appear between richer and poorer zip codes in states other than Minnesota due to unique approaches taken by various states in mitigating COVID-19 exposure.
| Main Category                  | Name                                                      | 2/03/20 - 3/16/20 | 3/16/20 - 6/01/20 | 6/01/20 - 11/23/20 | 11/23/20 - 1/11/21 | 1/11/21 - 5/31/21 |
|-------------------------------|-----------------------------------------------------------|-------------------|-------------------|--------------------|--------------------|-------------------|
| **Food Services**             |                                                           |                   |                   |                    |                    |                   |
|                              | Full-Service Restaurants                                 | 44.7%             | 74.5%             | 66.7%              | 68.3%              | 58.9%             |
|                              | Limited-Service Restaurants                              | 56.1%             | 55.7%             | 59.4%              | 54.6%              | 65.5%             |
|                              | Meat, Seafood, & Fruit/Vegetable Markets                 | 47.6%             | 34.1%             | 50.8%              | 50.7%              | 49.2%             |
|                              | Supermarkets & Grocery Stores                           | 42.3%             | 48.9%             | 60.4%              | 58.5%              | 57.8%             |
|                              | Gasoline Stations                                       | 52.7%             | 57.5%             | 56.1%              | 59.0%              | 43.7%             |
|                              | Plumbing, Heating, & AC Contractors                      | 43.5%             | 41.1%             | 38.4%              | 37.8%              | 55.0%             |
|                              | Offices of Physicians                                   | 46.0%             | 56.8%             | 59.4%              | 54.6%              | 54.6%             |
|                              | General Medical & Surgical Hospitals                    | 43.7%             | 54.6%             | 55.3%              | 48.2%              | 46.3%             |
|                              | General, Surgical, Psychiatric, & Specialty Hospitals   | 49.5%             | 41.5%             | 48.2%              | 43.0%              | 44.3%             |
|                              | Pharmacies & Drug Stores                                | 58.4%             | 42.9%             | 51.4%              | 43.0%              | 49.7%             |
|                              | Veterinary Services                                     | 49.6%             | 39.1%             | 51.6%              | 38.1%              | 54.8%             |
|                              | Nursing Care & Child Day Care                           | 50.4%             | 47.3%             | 58.8%              | 49.2%              | 63.8%             |
|                              | Funeral Homes & Services                                | 45.3%             | 41.5%             | 45.9%              | 38.6%              | 39.8%             |
|                              | Car and Other Vehicle Rental                            | 66.4%             | 33.9%             | 50.6%              | 43.3%              | 37.3%             |
|                              | Hotels & Motels                                          | 39.4%             | 58.0%             | 64.1%              | 54.8%              | 54.2%             |
|                              | Correctional Institutions                               | 64.8%             | 46.1%             | 42.9%              | 40.9%              | 46.6%             |
|                              | Police Stations                                         | 40.9%             | 36.4%             | 45.5%              | 27.3%              | 63.6%             |
|                              | Libraries & Archives                                    | 55.2%             | 38.8%             | 50.7%              | 39.5%              | 44.2%             |
|                              | Religious Organizations                                 | 46.2%             | 63.2%             | 62.3%              | 60.1%              | 57.3%             |
|                              | Barber Shops, Beauty & Nail Salons                      | 50.3%             | 46.3%             | 44.4%              | 38.7%              | 43.3%             |
|                              | Movie Theaters                                          | 60.5%             | 58.8%             | 66.0%              | 56.1%              | 64.9%             |
|                              | Fitness & Recreational Centers (Gyms)                   | 55.0%             | 48.7%             | 50.4%              | 52.7%              | 51.1%             |

Table 2 Percent of Difference in Differences less than 0 for each Period
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## Appendix

| Main Category                  | Name                                                  | No. locations in high-income zip codes | No. locations in low-income zip codes |
|-------------------------------|-------------------------------------------------------|---------------------------------------|--------------------------------------|
| Food Services                 | Full-Service Restaurants                              | 231                                   | 192                                  |
|                               | Limited-Service Restaurants                           | 142                                   | 87                                   |
| Essential Goods/Services       | Meat, Seafood, & Fruit/Vegetable Markets              | 67                                     | 18                                   |
|                               | Supermarkets & Grocery Stores                        | 164                                   | 124                                  |
|                               | Gasoline Stations                                    | 197                                   | 155                                  |
|                               | Plumbing, Heating, & AC Contractors                   | 28                                     | 18                                   |
| Medical Locations             | Offices of Physicians                                 | 126                                   | 93                                   |
|                               | General Medical & Surgical Hospitals                 | 23                                     | 43                                   |
|                               | General, Surgical, Psychiatric, & Specialty Hospitals | 34                                     | 46                                   |
|                               | Pharmacies & Drug Stores                             | 99                                     | 65                                   |
|                               | Veterinary Services                                  | 106                                   | 50                                   |
|                               | Nursing Care & Child Day Care                        | 149                                   | 73                                   |
|                               | Funeral Homes & Services                             | 30                                     | 35                                   |
| Travel Locations              | Car and Other Vehicle Rental                         | 30                                     | 12                                   |
|                               | Hotels & Motels                                      | 111                                   | 118                                  |
| Judicial Services             | Correctional Institutions                            | 21                                     | 44                                   |
|                               | Police Stations                                      | 11                                     | 4                                    |
| Miscellaneous                 | Libraries & Archives                                 | 75                                     | 65                                   |
|                               | Religious Organizations                              | 238                                   | 193                                  |
|                               | Barber Shops, Beauty & Nail Salons                   | 115                                   | 72                                   |
|                               | Movie Theaters                                       | 40                                     | 19                                   |
|                               | Fitness & Recreational Centers (Gyms)                | 156                                   | 69                                   |

*Table A 1 Relevant NAICS code and number of locations in each type of zipcode*
Figure A 1 Relative changes in the number of visits between low- and high-income zip codes for Hotels & Motels
Figure A 2 Visits to Full-Time Restaurants by Duration (minutes) from March 2020 to May 2021

Figure A 3 Visits to Limited-Service Restaurants by Duration (minutes) from March 2020 to May 2021