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The Efficiency of U.S. Public Space Utilization During the COVID-19 Pandemic

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The COVID-19 pandemic has called for and generated massive novel government regulations to increase social distancing for the purpose of reducing disease transmission. A number of studies have attempted to guide and measure the effectiveness of these policies, but there has been less focus on the overall efficiency of these policies. Efficient social distancing requires implementing stricter restrictions during periods of high viral prevalence and rationing social contact to disproportionately preserve gatherings that produce a good ratio of benefits to transmission risk. To evaluate whether U.S. social distancing policy actually produced an efficient social distancing regime, we tracked consumer preferences for, visits to, and crowding in public locations of 26 different types. We show that the United States' rationing of public spaces, postspring 2020, has failed to achieve efficiency along either dimension. In April 2020, the United States did achieve notable decreases in visits to public spaces and focused these reductions at locations that offer poor benefit-to-risk tradeoffs. However, this achievement was marred by an *increase*, from March to April, in crowding at remaining locations due to fewer locations remaining open. In December 2020, at the height of the pandemic so far, crowding in and total visits to locations were higher than in February, before the U.S. pandemic, and these increases were concentrated in locations with the worst value-to-risk tradeoff.

KEY WORDS: COVID-19; nonpharmaceutical interventions; social contact; social welfare; transmission risk

1. INTRODUCTION

The COVID-19 pandemic has called for and generated massive novel government regulations to generate social distancing (World Health Organization [WHO], 2020). The goal of these social distancing measures has been to reduce disease transmission. Transmission has been shown to occur when infected and noninfected individuals congregate, especially in crowded and poorly ventilated spaces (Cevik, Marcus, Buckee, & Smith, 2020; Chang et al., 2021). Examples of social distancing measures put in place include restrictions on maximum gathering sizes, stay at home orders, and restrictions on visiting locations and businesses based on type (e.g., schools and "nonessential" businesses) (Brauner et al., 2021).

A number of studies have attempted to guide and measure the effectiveness of these policies (Brauner et al., 2021; Chetty, Friedman, Hendren, & Stepner, 2020; Flaxman et al., 2020; Holtz et al., 2020; Kraemer et al., 2020). Papers with causal analyses have found large negative causal effects of shutdowns

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on social mobility (Holtz et al., 2020), economic output (Chetty et al., 2020), and disease spread (Brauner et al., 2021). In order to establish causality, many of these papers use some variation on difference-in-difference analysis, measuring the outcome of interest in the days before and after a policy is implemented. This approach is useful for establishing precise estimates of the short-term effect of policies. Ideally, all policy recommendations should be based on causal inferences. That being said, available approaches to estimating the causal effect of government policies have significant limitations. Their most important limitation is that, in an effort to distinguish between the impact of a policy on social distancing and nonfocal causes of distancing (i.e., due to the diffusion of information or fear) difference-in-difference analyses restrict their attention to a short window of time around the implementation of a policy.[1] Additionally, causal analyses, which typically harness a large number of similar policy implementation examples, can tell us little about the cumulative impact of unique and hard to classify government policies.

Here we tradeoff the clarity of a causal approach for the comprehensiveness of a descriptive analysis. We move beyond normative questions and short-term causal analyses to a different question: has the U.S. achieved an efficient social distancing regime, relative to a prepandemic baseline? To evaluate this question, we tracked consumer preferences for, visits to, and crowding in public locations of 26 different types.

Efficient social distancing requires at least two elements: (i) Implementing stricter restrictions during periods of high viral prevalence (WHO, 2020) and (ii) rationing social contact to disproportionately preserve gatherings that produce a good ratio of benefits to transmission risk (Benzell, Collis, & Nicolaides, 2020). In practice, element (i) means focusing reductions in visits to and crowding in public locations in months and regions with high viral spread. Meanwhile, element (ii) requires making sure that these reductions are concentrated in low-value-to-risk locations like gyms and liquor stores, which are often crowded but provide relatively little economic or consumer benefit (Benzell et al., 2020). This latter task is complicated by the fact that the benefit-to-risk ratio of a location type is a moving target—both the transmission risk and consumer desire for a location change over time.

We show that the United States' rationing of public spaces, postspring 2020, has failed to achieve efficiency along either dimension. In April 2020 the United States did achieve notable decreases in visits to public spaces and focused these reductions in locations that offer poor benefit-to-risk tradeoffs. However, this achievement was marred by an *increase*, from March to April, in crowding at remaining locations due to location shutdowns. And, after April, many public spaces reopened despite the number of active cases continuing to increase. In November 2020, during the worst phase of the pandemic to that point, the locations we track were only 5% less visited than in November 2019—before the pandemic. Further, these visits and crowding are increasingly concentrated in location types with below average benefit-to-risk. We do not take a stance on whether the overall level of social distancing is too high or too low, but this finding raises serious questions about social distancing policymaking and enforcement, and suggests new approaches are needed.

2. STUDY DATA AND METHODS

Following Benzell et al. (2020), we use mobility data from SafeGraph that tracks over 47 million smartphones across the United States. Safegraph tracks aggregate anonymized visits to over 6 million points of interest across the United States. These data have been a core resource in the academic literature on COVID-19 (Benzell et al., 2020; Chang et al., 2021; Holtz et al., 2020; Weill, Stigler, Deschenes, & Springborn, 2020). In line with this literature, we reweigh observed visits within each month as a function of the visitor's home census tract to estimate the total number of visits and visitors for each location by visitor age and duration (Benzell et al., 2020; Chang et al., 2021). We focus on the 26 most visited categories of locations excluding those with data quality issues. SafeGraph also provides information allowing us to calculate square footage of a location. We use these data to construct our cumulative danger index. The index combines the total number of visits to a location type, number of unique visitors and person hours of visits during crowding of more than one visitor per 113 sq ft (corresponding to the CDC's 6 foot social distancing guideline), for all individuals as well

[1] A common framing of this approach is the following: while government policies may be a function of social beliefs, which themselves have a direct effect on social distancing, the exact timing of government policies is plausibly random. Therefore, if belief changes diverge across polities slowly, a difference in difference across policy adopting and nonadopting states is a plausible estimator for the effect of the policy over short time horizons.

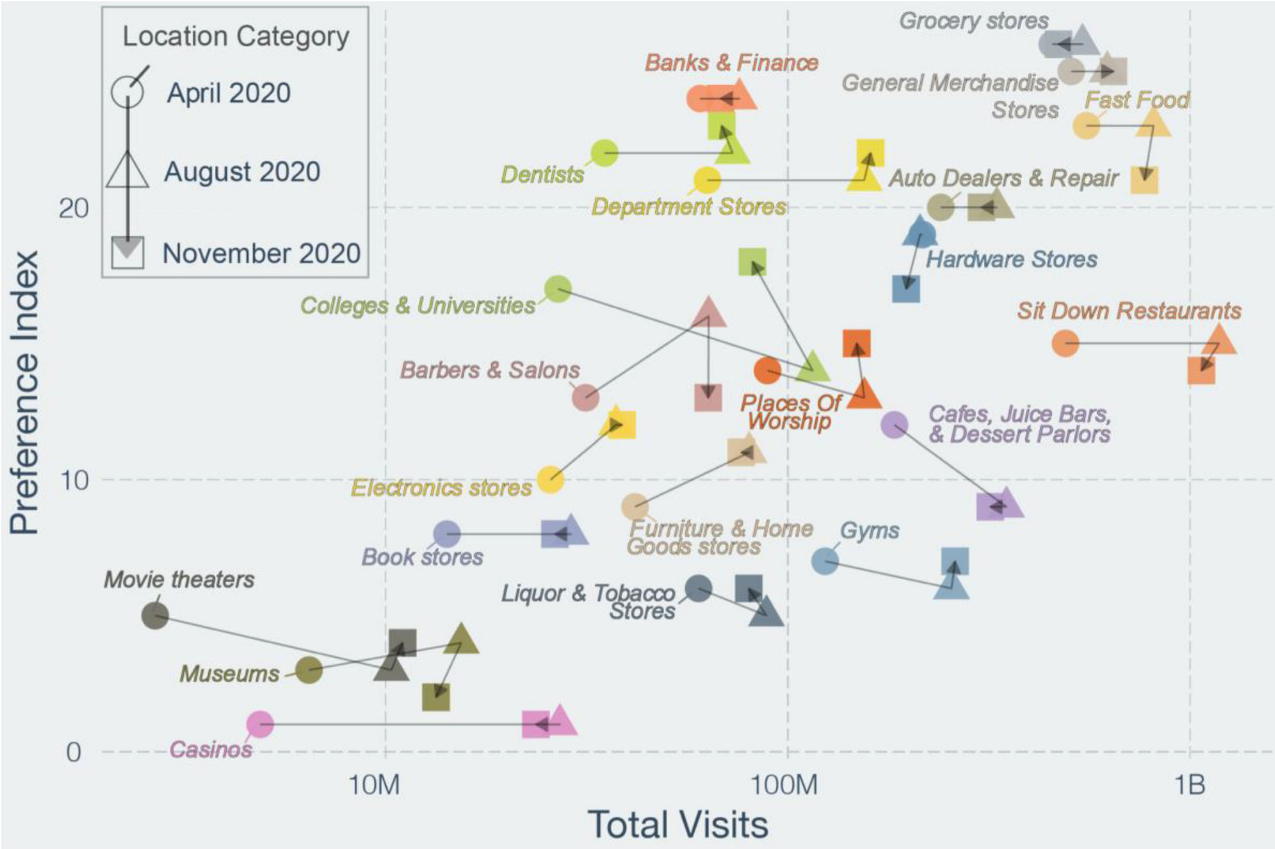

Fig 1. Tracking visits to and consumer value from public locations by type and month, selected location categories. See Fig. A2 for all location categories.

as those over 65, as well other factors (see Benzell et al., 2020 for details).

To measure the importance of a location to consumers, we conducted three waves of a nationally representative survey. Over 1000 respondents were recruited in each wave through Lucid, a market research firm widely used in research (Coppock, & McClellan, 2019). The three waves of the survey were conducted during April 13–15, 2020; August 19–21, 2020, and December 1–3, 2020.[2] In each survey, respondents took part in a series of pairwise comparison tasks where they select the location type they prefer to remain open (Louviere, Hensher, & Swait, 2000). The respondents were asked for their preference assuming that the locations were safe to visit (the survey instrument prompt is reported in Fig. A1). Locations were ranked by what share of comparisons in which they were preferred. In our cumulative benefit index, we augment our consumer preference data with measures of economic importance consisting of data on annual payroll, receipts, and employment by location type[3] (Benzell et al., 2020).

Fig. 1 reports how total visits (log scale) and consumers' relative value from visits to locations of different types have evolved from April to December 2020.[4] Predictably, across time periods, the figure displays a positive relationship between the value people place on being able to visit a location and the number of visits they make to a location. However, there is significant heterogeneity, with some locations

[2]In the figures below, November data utilize the December 1–3 preference survey wave, and dates in April and earlier use the April 13–15 preference survey wave.

[3]From the most recent edition of the U.S. census bureau statistics of U.S. businesses, retrieved at https://www.census.gov/data/tables/2017/econ/susb/2017-susb-annual.html. These data remain fixed throughout our time period of analysis. Retrieved on 12-21-20.

[4]A version of this figure with no location categories omitted is presented in Fig. A1.

being less valued per-visit (e.g., gyms) and some being more valued (e.g., banks).

For almost all location types, there were more visits to locations in November and August than April, despite surging active case rates. From April to August, the total number of visits to locations tracked increased 66%, with particularly large increases to restaurants, colleges, casinos, and amusement parks. In November 2020 there were 3.8 billion visits to locations, compared to 4.0 billion in November 2019. Hardware stores, which individuals flocked to at the start of the pandemic for masks and cleaning supplies, are the only location type to record a reduction in visits from April to November 2020.

Increases in visits to a particular location type are potentially justifiable through changing preferences. However, the ordering of location preferences over this period was highly stable. The most notable changes from the beginning to the end of the sample are fast food falling from fourth most important to sixth (after department stores and dentists) and moderate increases in rank for furniture and home goods and electronics stores, both of which advanced past office supply stores and cafes. Overall, the correlation coefficient between change in consumer preference rank and change in log-visits is -0.13 with 95%CI $[-0.39, 0.15]$.

Whatever overall level of reduced social contact one attempts to target, efficient social distancing policy requires a focus on reducing visits to locations that provide less value per visit. It also requires a focus on reducing visits during time periods of high viral spread. Fig. 2 evaluates the United States along both dimensions.

Fig. 2, panel A reports our overall measures of risk and benefit by location type in February and November 2020. These measures are cumulative, meaning that the danger and benefits are not per-visit, but from all visits. The measures are also relative and within-month. The danger indexes combine nine measures of crowding, visits, and social mixing across geographies and age groups. The benefit index combines our consumer preference ranking with three measures of economic importance.

Also plotted in panel A is a 45° line and lines of best fit by month. Locations in the upper left corner give better than average benefits-to-costs, and the opposite holds for those in the bottom right corner. Theoretically, efficient usage of rationed social contact would require all points to lie directly on the 45° line in November.

As is shown by the November line of best fit slanting further away from 45°, there has actually been a *deterioration* in allocative efficiency. Our data are a census, so this observed deterioration could not have been caused by selecting an unrepresentative sample by chance. That being said, our observations of visits to locations are noisy for various reasons, perhaps most importantly due to randomness in when people decide to have their phones on or off. If this noise is assumed to occur at the individual visit or individual location level, our confidence in the deterioration of the line of best fit is highly significant.[5] Allocative efficiency in public location rationing improved moderately from February to April, but the mix since November is worse than before the pandemic began (Fig. A3 reports the correlation between relative cumulative benefit and risk over time). A set of important location categories driving this result are the three restaurant varieties in the data (sit down, fast food, and cafes). Each of these categories had below average benefit/risk tradeoffs at the beginning of the pandemic, and all saw decreases in relative value and increases in relative risk.[6]

The United States has also failed to ration social contact across time. Fig. 2 panel B plots active cases in the United States against two measures of cumulative transmission risk for three categories of locations. The danger measures are total visits and person-hours of crowding at a density preventing 6-foot rule compliance. Locations are split into three categories by whether they have above, below, or close to average benefit-to-cost ratios (Table AI reports how location types are classified). Active cases are indexed to one on December 31, 2020, while the

[5] Treating each location type's tradeoff as being observed a number of times equal to its number of locations yields a February 2020 95% confidence interval of [0.3616997, 0.3642804] and a 95% confidence interval for the slope for November 2020 of [0.3003999, 0.3028987]—assuming noise is at the visit level generates even tighter confidence intervals.

[6] In an Appendix, we investigate whether this effect is driven by locations that consumers feel to be most essential. Fig. A4 splits Fig. 2 panel A into two location categories—the five that consumers rank as most important in surveys and the 21 other locations. As can be seen, the decrease in correlation between location risk and value is driven largely by a decrease in relative cumulative danger from banks, alongside a simultaneous decrease in relative cumulative importance and increase in relative cumulative risk from fast food restaurants. The arguably essential location categories of hospitals, homes, day care, and schools are excluded from the analysis, generally because of data quality issues (*1*). Hospitals are excluded from the analysis, because crowding and visits to hospitals will necessarily increase during a pandemic.

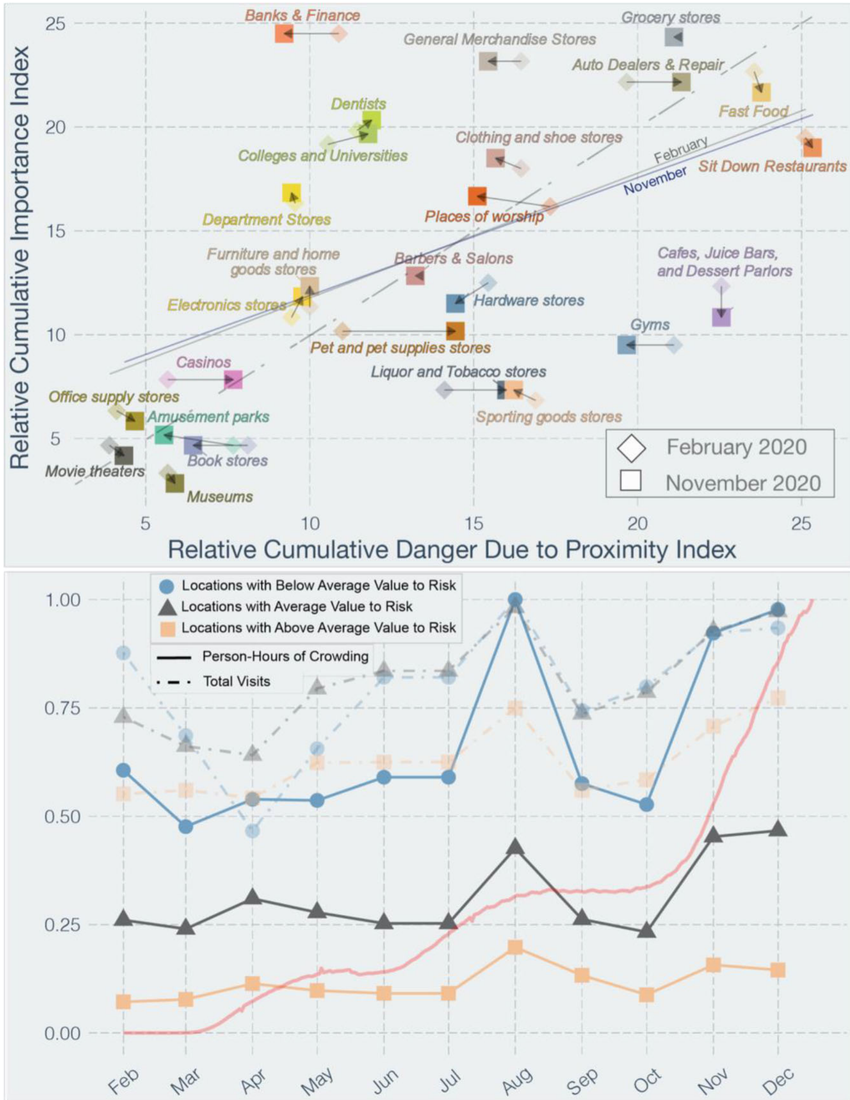

Fig 2. Panel A: Relative economic importance and transmission risk by location type in February and November 2020. Panel B: Visits to and person-hours of crowding in locations categorized by benefit-to-risk ratio over time. Total visits and person-hours of crowding are indexed, each taking the value of one for below-average value to risk locations in August 2020. Active COVID-19 cases are indexed to one on December 15th 2020.

transmission risk measures are indexed to one for the poor-value-to-risk category in August.

Panel B shows a clear positive correlation between transmission risk measures and active cases. Across all location types, crowding and visits increased from February to November, as active cases surged. In March and April there was a large decrease in visits to locations, especially particularly bad-tradeoff locations, as well as in early autumn. However, the success of April was marred by an increase in crowding, from March to April, in all location categories. The decoupling of crowding and visits in the spring is consistent with economic tracking data. By April 15, consumer spending had decreased 14.5% from seasonally adjusted average level in January 2020, while 42.9% fewer small businesses were in operation (see Fig. A5 and Chetty et al., 2020).

The fall reduction in visits to poor tradeoff location types, despite being mistimed, were fortunately not associated with an increase in crowding. This is not due to a decrease in economic activity, but rather because of increases in purchases through online platforms, better space utilization across locations, and an increase in the number of small business locations remaining open. However, in December, indexed crowding again increased to a level higher than visits. By mid-November, reopenings raised the number of small business locations to 28.1% below their January level, while retail spending was 15.3%

higher (Chetty et al., 2020). The combination of fiscal stimulus, social distancing regulations, and private risk decisions, especially in the spring, conspired to create a worst-of-all-worlds outcome, with increasing consumer demand concentrated into a reduced number of physical locations.

3. DISCUSSION

Has the United States properly utilized its suddenly precious access to public spaces? Rational social distancing policy seeks to equalize value to infection risk across location types and time. April, early in the pandemic, a nationally coordinated “30 Days to Stop The Spread” successfully led the United States to reduce visits to public locations, and especially those with poor value-per-visit such as gyms. Causal analyses of shutdowns typically focus on this relatively successful period, painting an incomplete picture. Since then, with the partial exception of the early fall, the efficiency of social distancing has been in decline. Due to a combination of diminished enforcement, a lack of social and individual will, eased regulation, and fiscal stimulus, the United States has increased the number of visits to a reduced number of locations. The deterioration of national coordination past the spring, essential for addressing interregional externalities, likely played a large role in this incoherent outcome (Cevik et al., 2020; Woodward, 2020).

Our analysis does have limitations. Seasonal effects, the introduction of nonpharmaceutical interventions (NPIs) other than social distancing measures (e.g., masks and better usage of outdoor spaces like courtyards and takeout windows), and improving hospital treatments (Benzell, Collis, Nicolaides, & Bardhan, 2020) are unincorporated factors that also shift the relative value and risk of personal contacts across time (see Fig. A7). However, medical knowledge and compliance with mask usage are not dramatically higher in winter than July (see Fig. A6), and other NPI behavior observance that we can track has remained constant (Collis et al., 2021). Across location types, efficiency calls for equating *marginal* value and *marginal* danger ratios, something we proxy only imprecisely with measures of *average* value and risk. Our data also do not cover some aspects of social distancing, such as meetings in private homes, but it is unlikely that density in and visits to these unregulated private spaces have been reduced with greater success than public spaces (see Fig. A8). We present seasonally adjusted data, complementary evidence on other NPI compliance and economic outcomes, and geographic breakdowns by state and urban-rural of our findings in the Appendix (see Figs A9 and A10).

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APPENDIX

Many types of stores, locations and institutions have been closed because of COVID-19. In this study, you will be asked to make a series of decisions about locations. In each decision, you are asked to choose the location you most prefer among two options – regardless of whether that location is currently open. Assume that it is safe to visit these locations. You will make a total of 30 decisions.

Many types of stores, locations and institutions have been closed because of COVID-19. Consider the following two types of locations.

Whether or not the location is currently open, which is the most important for you to be open?

Fig A1. Consumer preference survey instrument prompt.

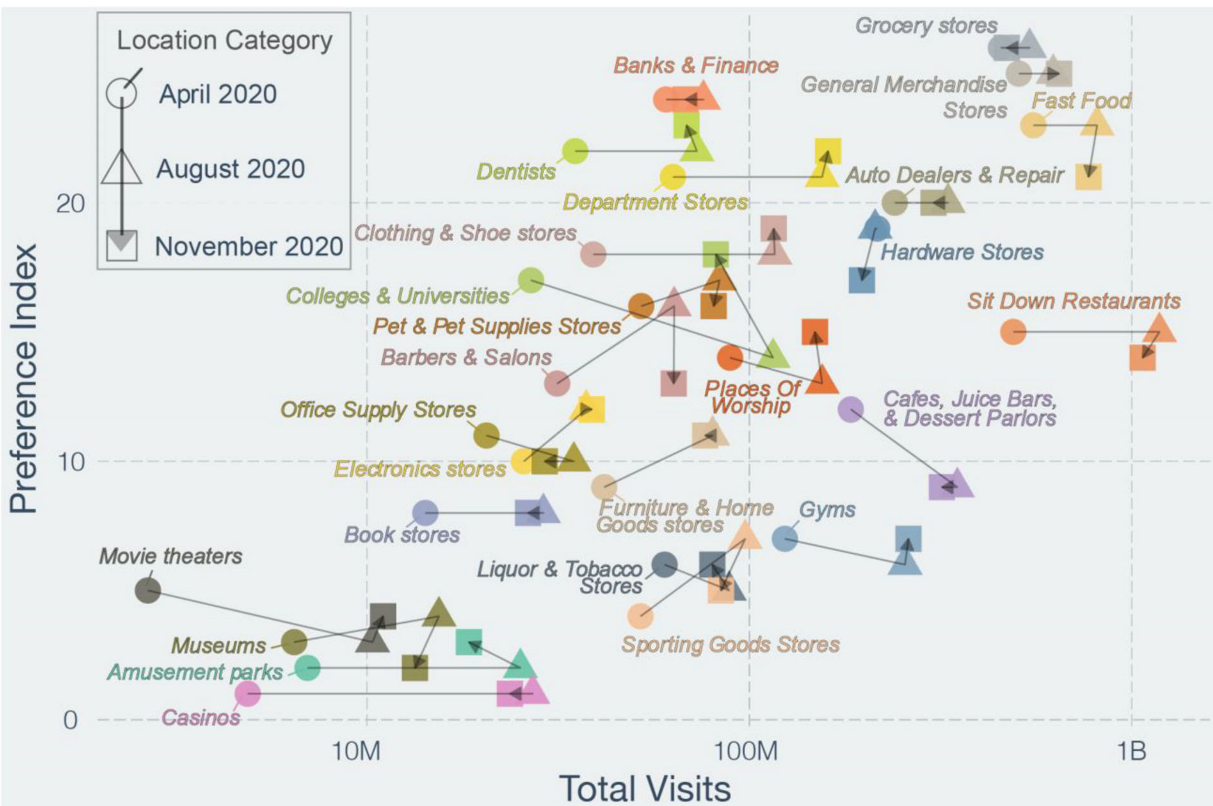

Fig A2. Tracking visits to and consumer value from public locations by type and month, all location categories.

Table A.1. This table documents which locations are in which category for Fig. 2B, and Fig. A11

Locations with above average value to risk (27% of total visitation)	Grocery stores, dentists, colleges and universities, banks & finance, general merchandise stores, department stores
Locations with average value to risk (36% of total visitation)	Fast food, auto dealers & repair, barbers & salons, places of worship, pet and pet supplies stores, clothing and shoe stores, hardware stores, electronics stores, furniture and home goods stores, casinos, book stores, museums, office supply stores, movie theaters, amusement parks.
Locations with below average value to risk (36% of total visitation)	Sit down restaurants, cafes, juice bars, and dessert parlors, gyms, liquor and tobacco stores, sporting goods stores

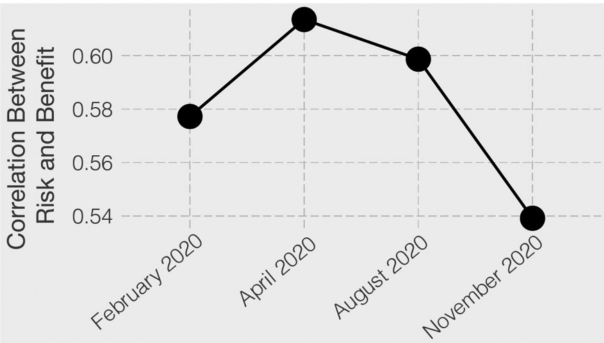

Fig A3. This figure reports the correlation between our relative cumulative risk and benefit indexes for a sample of months. April and August improved on February's allocative efficiency somewhat, but November was worse. February, before our study's first wave, uses April consumer preference survey data.

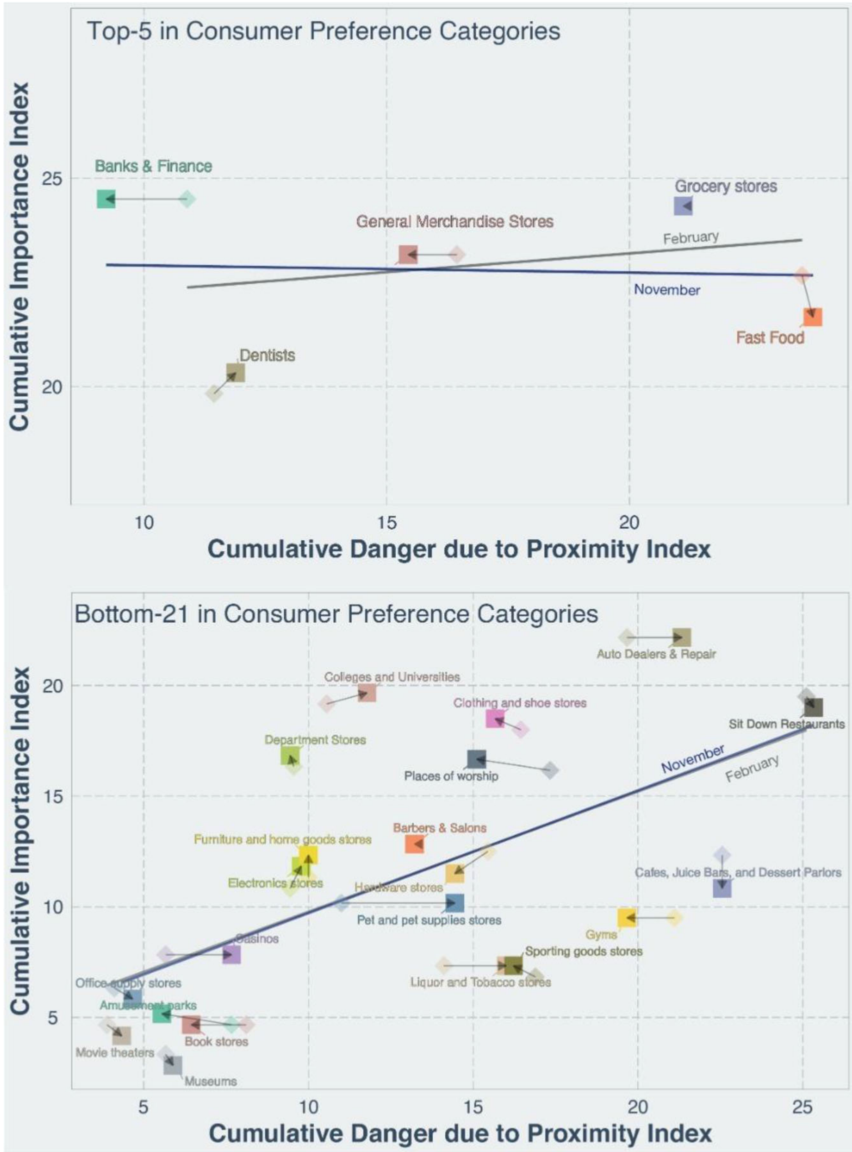

Fig A4. Relative economic importance and transmission risk by location type in February and November 2020, splitting data into the five categories rated as most important in consumer preference surveys and the 21 other location types.

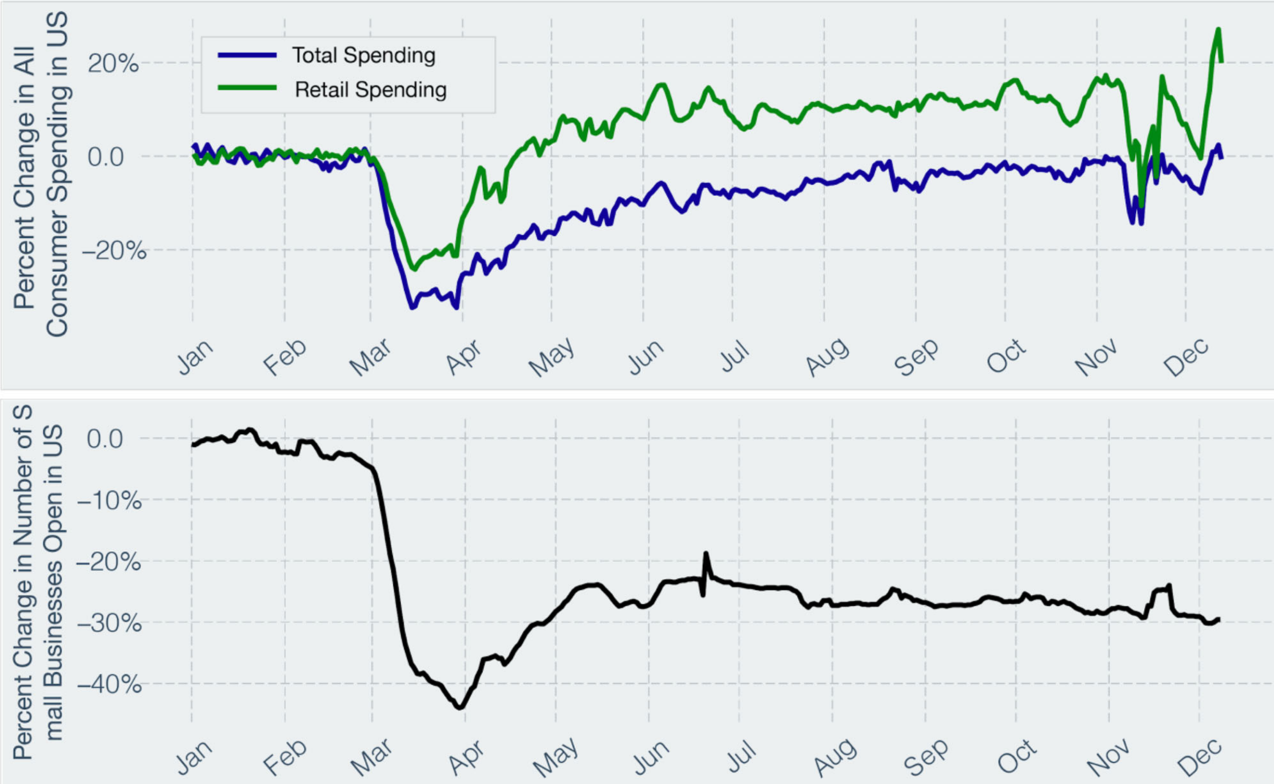

Fig A5. Retail spending and small business locations open over time. Data retrieved from "Track the Recovery" https://tracktherecovery.org/ (Chetty et al., 2020). Seven-day moving averages seasonally adjusted and indexed to January 4–31 2020.

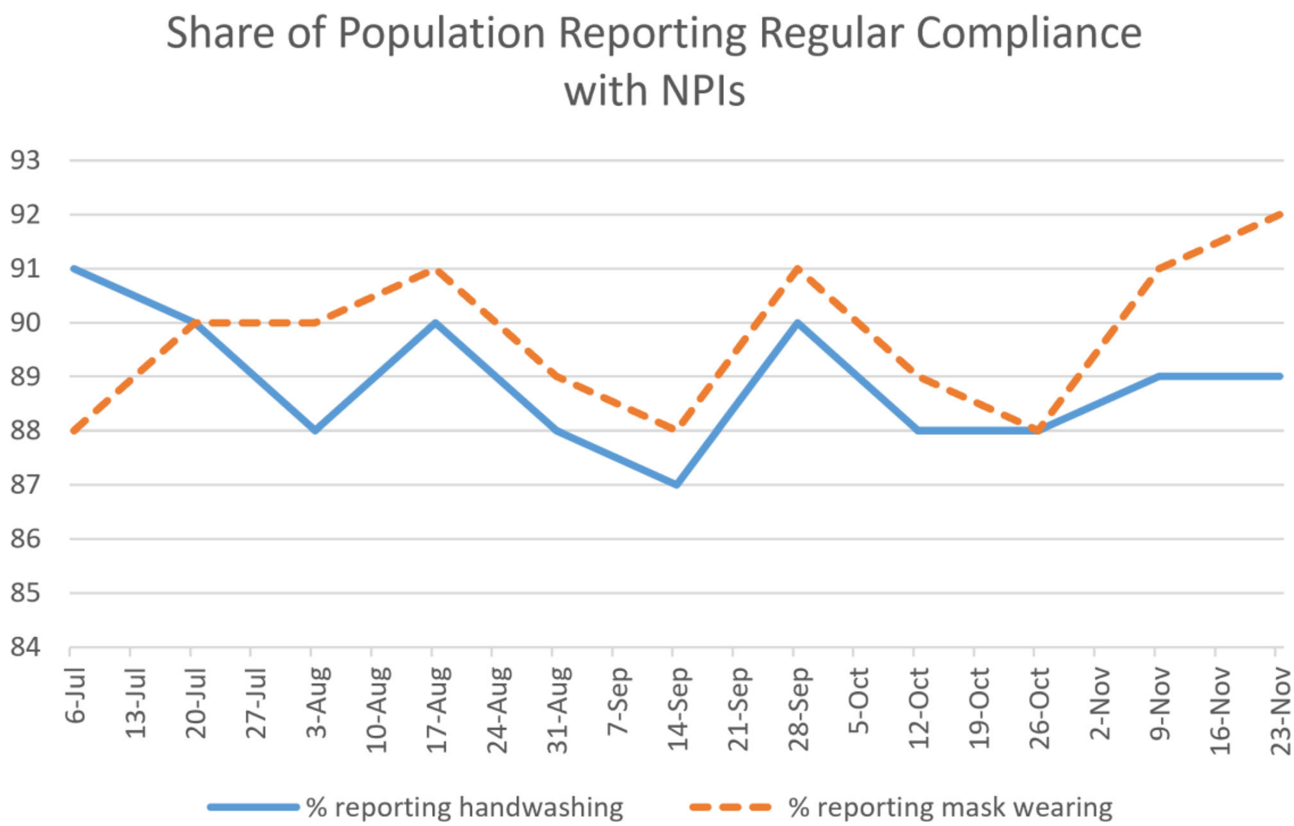

Fig A6. Percent of people in the United States (based on a representative sample of U.S. internet population recruited on Facebook (Collis et al. 2021) who report wearing masks and practicing handwashing to prevent the spread of COVID-19

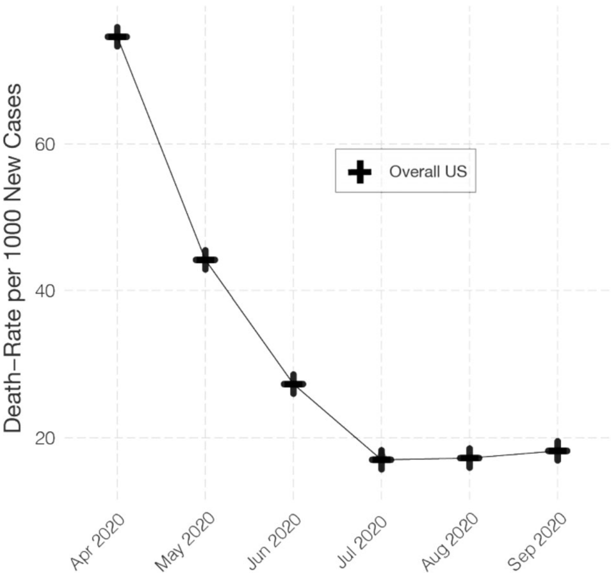

Fig A7. U.S. COVID-19 Deaths per thousand cases. Data from COVID-19 data repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. Reproduces a figure in Benzell et al. (2020).

Fig A8. Total time spent outside home. Retrieved from "Track the Recovery" (https://tracktherecovery.org/; Chetty et al., 2020). GPS mobility data indexed to Jan 3–Feb 6, 2020 from Google COVID-19 Community Mobility Reports. These data are not seasonally adjusted.

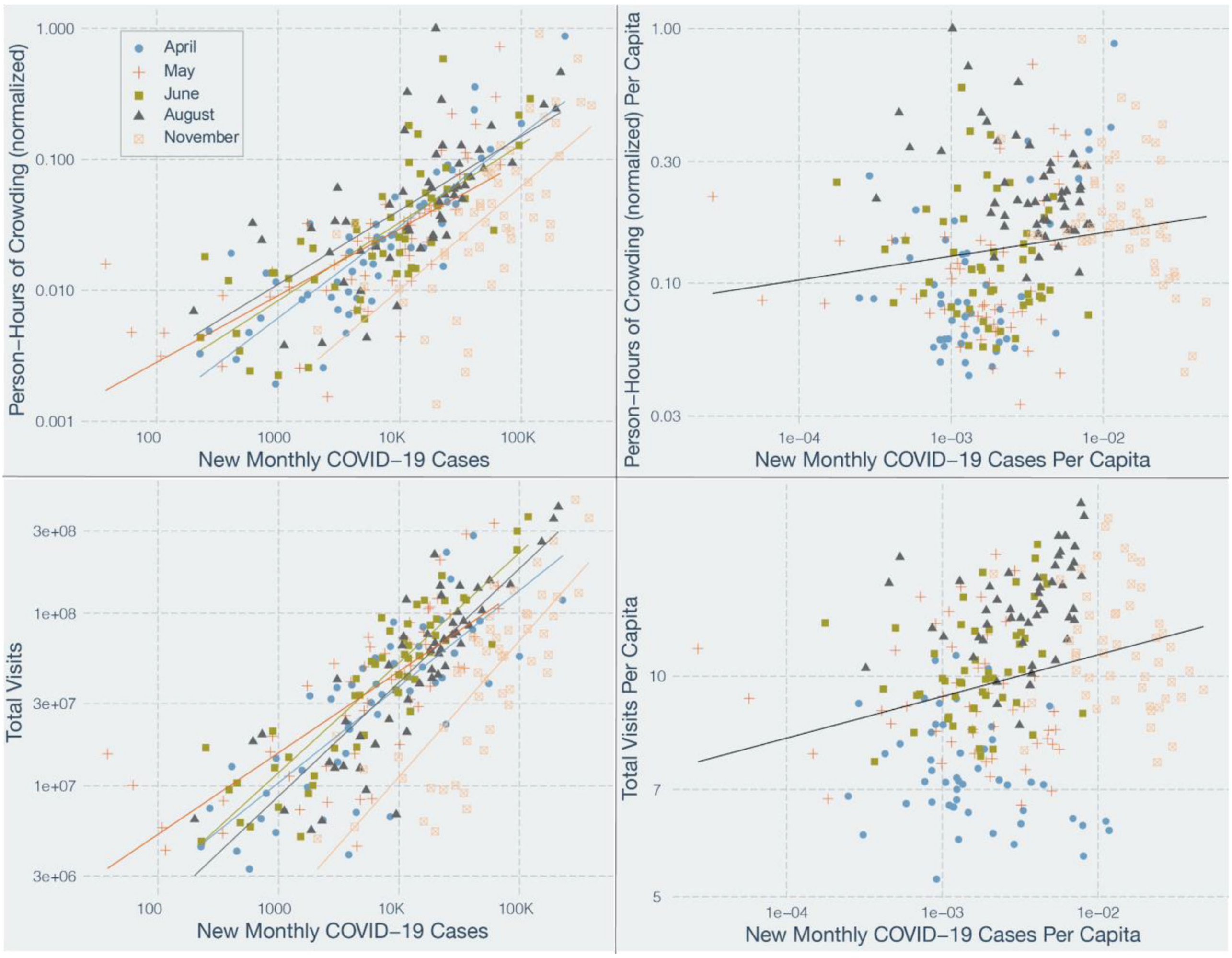

Fig A9. Scatter plot of transmission risk measures against new cases (either raw or per-capita) at the state-month level. Each figure has 250 data points (5 months, 50 states). Left hand side panels are reported in levels, and right hand side panels are reported per-capita. Active case data at the state level are not available.

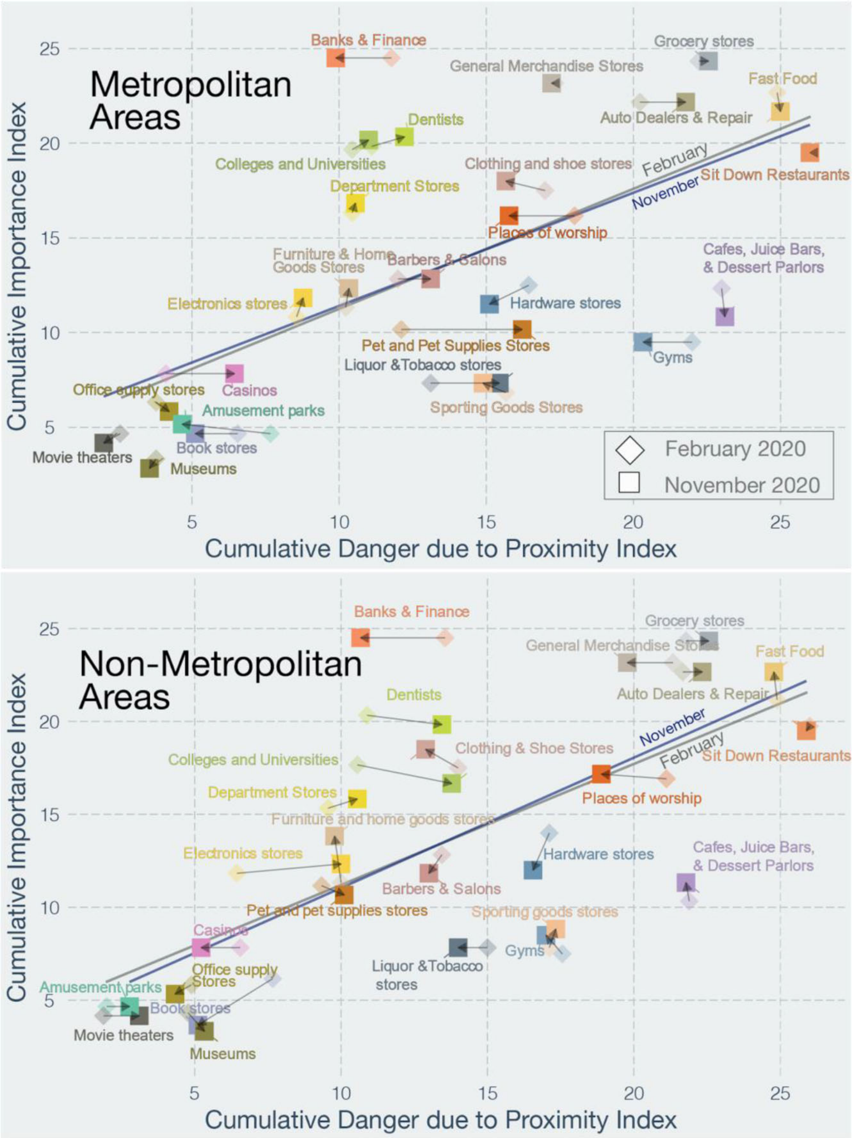

Fig A10. This figure follows Fig. 2, panel A, but with an urban-rural split. Counties in the United States are divided by urban-rural using RUCC codes, with counties of RUCC code 4–9 classified as rural, and 1–3 classified as urban. Both consumer welfare surveys and proximity danger indexes have regional data, but economic census data are only available nationally.

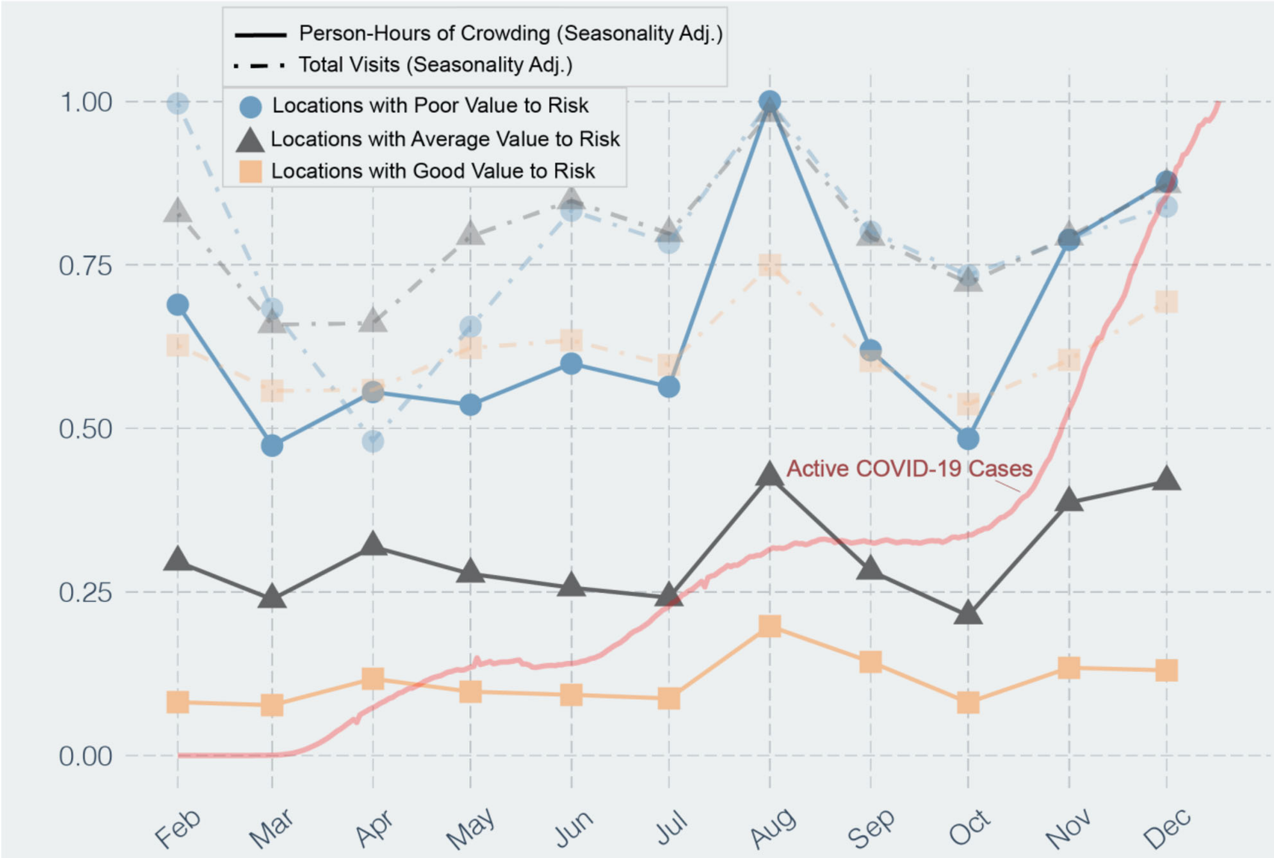

Fig A11. This figure follows Fig. 2, panel B, but seasonally adjusts danger measures. Seasonal adjustment indexes Feb 2019 total visits to all Safegraph locations to one, and divides 2020 outcomes by this measure.