Rationing Social Contact During the COVID-19 Pandemic: Transmission Risk and Social Benefits of US Locations

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This draft: April 26, 2020
First draft: April 18, 2020

Abstract

To prevent the spread of COVID-19, some types of stores and gathering places have been shut down while others remain open. The decision to shut down one type of location and leave another open constitutes a judgement about the relative danger and benefits of those locations. Using location data from a large sample of smartphones, nationally representative consumer preference surveys, and government statistics, we measure the relative transmission risk benefit and social cost of closing about thirty different location categories in the US. Our categories include types of shops, entertainments, and public spaces. Our main analysis ranks twenty-six categories by those which should face stricter regulation via dominance across eight dimensions of risk and importance and through composite indexes. We find that from February to March, there were larger declines in visits to locations that our measures imply should be closed first. We hope this analysis will help policymakers decide how to reopen their economies.

1 Introduction

"Society is commonly too cheap. We meet at very short intervals, not having had time to acquire any new value for each other. We meet at meals three times a day, and give each other a new taste of that old musty cheese that we are."

Henry David Thoreau, *Walden*

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§We thank Jonathan Wolf and the rest of the team at SafeGraph for data. We are indebted to Erik Brynjolfsson, Sinan Aral, Dean Eckles, and the researchers at the MIT Initiative on the Digital Economy for invaluable feedback. We additionally thank the MIT Initiative on the Digital Economy for research funding. We thank Victor Yifan Ye for help with visualizations. We thank Maxwell H. Levy M.D. for medical insights. We thank Manuela Collis for helpful feedback on survey design. Our consumer survey was determined to be exempt by MIT's IRB (project number E-2115).

COVID-19 is primarily spread by droplets of mucous and saliva from those who are infected.[1] Infected people are often asymptomatic [Bai et al. (2020)], meaning that in the absence of a comprehensive system test and trace individuals by infection status, all physical proximity across different households is potentially dangerous. A good way to think about this challenge is as an increase in the social cost of physical proximity. Gatherings should be regulated to achieve a target R_0, the number of people an infected person goes on to infect. Indeed, polities have already implemented a wide variety of new regulations on work, locations and gatherings.

We conceptualize the decision to shutdown a location as a tradeoff between infection risk and economic and social costs. In this paper we make an empirical contribution regarding which types of locations pose the best and worst risk-reward tradeoffs. While other analyses have focused on the important questions of the effectiveness of government action on social distancing [Allcott et al. (2020)] or when to re-open economies [Alvarez et al. (2020)], we focus on a descriptive question. We aim to inform policymakers about their portfolio of options of what to re-open as they attempt to reach a target R_0 at the minimum social cost.

To do so, we combine several measures of the importance and danger of categories of stores and locations. We consider about thirty categories of location, from fast-food restaurants, to museums, to grocery stores. Juxtaposing the danger and importance of these locations yields a ranking of what should be opened earlier versus later in the economic restart process. We then compare our ranking to which types of locations have seen the largest actual reductions in attendance.

Our data comes from three main sources. The danger of a location due to physical proximity is derived from *Safegraph*. Safegraph tracks the movement patterns of tens of millions of Americans at the monthly level. It categorizes locations into categories by NAICS industry. We select thirty of these categories to further investigate. We measure the amount of physical contact (and danger) of a location through four main measures: number of visits, number of unique visitors, and person-hours of visits above two density thresholds. These last measures are inspired by the CDC's 'six-foot' social distancing rule and the rule of 1 customer per 20 square metres implemented in parts of Germany.[2]

We think of the benefits of a location as coming from its consumer and producer surplus. We measure the relative consumer surplus from a location by conducting discrete choice experiments on a nationally representative sample of US residents. We measure producer surplus through a location type's total employment, receipts and payroll as measured by the US Census.[3] While we report supplementary data for all

[1] The World Health Organization, retrieved 4-16-20.

[2] CDC "How COVID-19 Spreads" retrieved 4-16-20; What you need to know about plans for Germany's states to ease lockdown retrieved 4-17-20

[3] Many public economic analyses of welfare exclude (or include negatively) direct changes in labor costs in evaluating a policy. The logic of this is that, during full employment, the wage of a worker is also an opportunity cost – the worker would be able to make the same wage employed elsewhere. However, during this crisis there is dramatic underemployment. Furloughed workers are being supported by the government at tremendous expense. Therefore, the work forces of these industries can be considered as having very low opportunity costs and their production should be counted in social surplus.

thirty categories, ultimately data quality concerns lead us to omit four categories from the main analysis.

With these measures of the importance and danger of a location in hand, we evaluate categories of location using two methods. First, we consider dominated and dominating options. If a category is better than another along all dimensions of danger and importance, then it should face looser regulation. This is our most conservative set of results. We find electronics and furniture stores should be reopened before (or simultaneously to) sporting goods and liquor and tobacco stores. Banks should be reopened before many types of locations, while cafes and gyms should be seventh in line at most. Places of worship should be opened before gyms but after colleges and universities.

For a single-dimensional look at the tradeoffs of each location, we also introduce indexes of danger and importance combining all of our measures. Unsurprisingly, the danger of a location (which is determined in large part by the frequency and length of visits) is positively related to importance. However, the relationship is not perfect, and we identify outliers in the overall relationship as candidates for tighter or laxer regulation.

We evaluate these indexes separately for metro and non-metro locations. We also estimate an alternate danger index for only visitors aged over 65. Across these three variations, differences in the importance-danger tradeoff by category are minimal. Locations our analysis implies should face relatively lighter restrictions are banks, general merchandise stores (e.g. Walmart), and colleges and universities. Locations our analysis implies should face relatively strict restrictions are gyms, cafes, liquor and tobacco stores, and sporting goods stores.

It is important to emphasize the limitations of this analysis. One of the most important is that we ignore potential economic linkages, social welfare externalities, or visit substitution across different industries. We acknowledge these limitations throughout. We conclude with a discussion of how our analysis contrasts with policies which are currently being implemented.

2 Data

We initially selected thirty categories of locations to study. These locations are reported in Table S1.[4] They correspond to NAICS industry categories or combinations thereof. These locations were selected for being among the most visited types in our geolocation data. We excluded from our analysis several essential categories related to housing, healthcare, elderly care and categories related to travel. We collect data of three types. These are data on the category's transmission risk, economic output and costs, and consumer value.

[4]Note that names of these categories are shortened in the text for brevity.

2.1 Cumulative Transmission Risk by Location Category

To quantify the potential contribution of a location to disease transmission (i.e. its *danger*) we utilize a fine-grained dataset of geolocations from approximately 47M smartphone devices in United States. The data are collected by Safegraph and record visitation patterns to around 6M points of interest on a daily, weekly and monthly basis. Our primary analysis focuses on February and March 2020. This data has been previously used to study political polarization [Chen and Rohla (2018)], racial segregation [Athey et al. (2019)] and the impact of open-bathroom policy enacted by Starbucks on foot traffic [Gurun et al. (2020)].

The "visitation" data includes information about the total number of visits, total number of visitors, and timing and length of visits. Only information from devices associated with individuals over the age of 13 are reported for privacy reasons. The "points of interest" data includes information on location (full address), six-digit NAICS code, and branding. For each location, SafeGraph also provides data on the space's geometry. We use this to calculate the area of a location in square feet.[5]

The thirty location categories of interest we focus on account for ∼64% of all unique visits from January 2019 through March 2020. Out of all categories, full service restaurants (sit down) is the most popular in terms of both number of visits and unique visitors. The least popular according to the same metric is bars and nightclubs (see Table S1). Between February and March 2020 we observe a 24.9% drop in the total number of visits at all places of interest included in analysis, reflecting the social distancing measures which began to be implemented in March. We supplement the SafeGraph data with census data to classify locations by metro and non-metro regions using the 2013 RUCC classification scheme.[6] To account for the fact that SafeGraph is tracking only a fraction of all the individuals in the US, we upscale every SafeGraph visit to approximate the *real* number of visits/visitors for each location.[7] For each individual location, we calculate the number of person-hours of visits per square foot for any hour in a day.[8]

We create four main monthly level measures of a location's danger. These are:

- Total visits
- Total unique visitors

[5]Note that SafeGraph's geometry data is two-dimensional, so we under-count the effective floor-space of locations with multiple stories.

[6]US Department of Agriculture, retrieved 4-16-20

[7]Specifically, we use SafeGraph visit source data to estimate the home county of every visitor to a location (Only visitors from counties with at least five visitors are reported for privacy purposes. We impute the remaining visitors as being from the home county of the location). We then use the ratio of devices tracked by SafeGraph in a county to that county's population aged over 13. In the initial draft of this paper, we uniformly rescaled each visit by 7.01, reflecting the ratio 328M US population over 46.8M devices tracked. This change in rescaling makes no significant difference to the results.

[8]For a given place of interest, the person-hours of visits per square foot for a specific hour in a day is calculated as the average daily number of visits multiplied by the mean duration of a visit, multiplied by the relative popularity of that particular hour and divided by square footage. The mean duration of a visit is not directly reported by SafeGraph, but is inferred from the visit length bins provided.

- Person-hours of visits during crowding of more than 1 visitor per 113 sq. ft.[9]
- Person-hours of visits during crowding of more than 1 visitor per 215 sq. ft.[10]

To identify the danger of the category of interest, we sum the individual measures of all locations within the category.[11] The danger indexes we construct in this way are *cumulative* in the sense that they do not represent danger-per-visit or danger-per-store, but rather the aggregate risk from all locations in a category.

There are many limitations of this risk data. Importantly, these measures do not take into account heterogeneity in types of visitors. Older visitors may be at more direct risk from visiting dense locations. There is also heterogeneity in from how far away a visit to a location is. Visitors from distant places might spread the disease to a county that had been previously untouched. These risk measures also do not take into account that some types of locations offer services (like dentists and barbers) that require intense physical proximity. Each of these three limitations we address in more detail in the discussion.

A limitation to our location risk data that we cannot account for is that it does not consider possible complementarity and substitution across locations. If one type of location (say grocery stores) were shut down, it might lead to increased visits and crowding in another type of location (say general goods stores).

2.2 Cumulative Economic Importance by Location Category

Our economic data comes from most recent edition of the SUSB Annual Data Tables by Establishment Industry.[12] Our measures of economic importance consist of annual payroll, receipts, and employment. Across our thirty categories there are 34.4 million employees, 1.14 trillion dollars in annual payroll, and 5.79 trillion in annual receipts.

Across our thirty categories there are 1.548 million firms and 2.165 million establishments, compared to 3.191 million SafeGraph points of interest. The fact that the number of establishments is similar to, and in fact smaller than, the amount of points of interest tracked by SafeGraph for these categories gives us confidence that we have a very high rate of coverage. Supplementary figure S1 plots the number of SafeGraph points of interest against the number of Census establishments. The number of SafeGraph points of interest is usually higher, due to the fact that multiple

[9] A six-foot radius circle

[10] German social distancing guideline of 1 customer per 20 square metres, retrieved 4-16-20

[11] We also consider several additional measures not currently used in the analysis. The first is the total person-hours of visits. The latter are alternative measures of density that count any individuals in a building for a part of an hour as contributing to crowding for the full hour. We also consider variations of the density threshold to account for different epidemiological views about safe distance [Bourouiba (2020)]. Figure S5 ranks locations by danger in February and March 2020. The danger ranking used is person-hours of visits during crowding of more than 1 visitor per 113 sq. ft. The changes between the ranking reflect in part social distancing measures imposed in mid-March and their heterogeneous impact on the different categories. For an alternate look into physical proximity of customers in various types of retail outlets using SafeGraph data, see [Goldfarb and Tucker (2020)].

[12] https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/documentation/. Created by the U.S. Census Bureau. 2017 data. Retrieved 4-16-20.

buildings in the same complex might be considered multiple points of interest but a single establishment.[13]

The four locations with the greatest divergence between census establishments and SafeGraph points of interest are "Bars and nightclubs," "Banks and other Financial Services," "Public and Private Schools," and "Parks and Playgrounds." Two of the outliers, "Public and Private Schools," and "Parks and Playgrounds" have dramatically more points of interest than census locations. The latter two are undercounted in the Census data because most of the examples of these location types are public. For example, the National Center of Education Statistics' count of all public and private schools is 130.9 thousand in the 2017-2018 school year, with 32.4 thousand of these being private.[14] The total figure is close to 116.9 thousand points of interest tracked by SafeGraph, and the private school number is closer to 22.1 thousand establishments tracked by the census.

The other pair of outliers, bars and banks, have surprisingly low SafeGraph point of interest counts. However, the number of SafeGraph points of interest, 83.9 thousand, is pretty close to the number of US bank branches in 2018 (88.1 thousand).[15] The low count for banks seems due to peculiarities in how the Census counts establishments. The census count likely includes many locations that are not designed for visitors (e.g. unlisted back-offices), as well as potentially some types of financial institutions that SafeGraph does not capture well. The very low point of interest count for bars and clubs, a mere 6.7 thousand points of interest for the entire country, is more troubling from the perspective of our analysis. SafeGraph staff suggest that part of the low count is due to ambiguity in the division between restaurants and bars and pubs that serve food.

While each of our categories are perfectly matched to this data, additional limitations remain. First, economic activity in different industries might be differently impacted by a shutdown. For example, shutting down all bank branches and physical locations would likely reduce their economic output by less than doing the same for barbershops. We partly address this concern in the discussion. Second, unlike our other sources of data, our economic importance data does not vary at the regional (metro vs. non-metro) level. A final important note is that we incorporate no data about linkages or complementarities between industries. If one industry is shut down, it could decrease the revenues and employment of another (e.g. by depriving them of an important input) or increase them (e.g. by effectively 'raising the cost' of a close

[13] The census definition of an establishment is "a single physical location at which business is conducted or services or industrial operations are performed. It is not necessarily identical with a company or enterprise, which may consist of one or more establishments. When two or more activities are carried on at a single location under a single ownership, all activities generally are grouped together as a single establishment. The entire establishment is classified on the basis of its major activity and all data are included in that classification. Establishment counts represent the number of locations with paid employees any time during the year." So physical locations without an associated employee (perhaps because it is only staffed by floating workers) should have a SafeGraph point of interest, but not be counted as an establishment.

[14] National Center of Education Statistics, retrieved 4-22-20.

[15] JLL Research, retrieved 4-22-20

substitute). In the current analysis we effectively assume that all industries are perfect substitutes.

2.3 Consumer Welfare Importance by Location Category

We conducted a nationally representative survey of 1,099 US residents. Respondents were recruited through Lucid, a market research firm, during April 13 to April 15, 2020. The sample is representative by age, gender, ethnicity and region [Coppock and McClellan (2019)]. The respondent's locations (zip-codes) are validated and directly provided to us by Lucid.

Each respondent takes part in a series of discrete choice experiments [Louviere et al. (2000)] where they choose which location, among two options, they would prefer to be open whether or not the location is currently open (see supplementary Figures S2 and S3 for the experiment instructions and a sample choice experiment). Discrete choice experiments have been widely used to measure valuations of market and non-market goods. This specific type of discrete choice experiment is single binary discrete choice [Carson and Groves (2007)]. To make responses consequential and incentivize respondents to respond truthfully, we gave them a chance to earn an additional monetary reward which is linked with their choices [Carson et al. (2014)].

Each respondent participated in a series of thirty single binary discrete choice experiments. We solicited a total of 32,970 decisions. For each location category, we compute the probability of a respondent preferring that location over other locations. We separately calculate these probabilities for respondents living in metro and non-metro areas (see Figure S4 for a list of locations ranked by consumer welfare importance and Table S2 for differences in importance for metro and non-metro areas).

3 Analysis

We now juxtapose how different locations fare along our four dimensions of importance (consumer importance, employment, payroll, receipts) and four dimensions of transmission risk (visits, unique visitors, person hours at moderate density, person hours at high density). The core idea is that locations that score higher in importance and lower in transmission risk should be prioritized. We exclude from this analysis four categories of location with data quality concerns.[16]

3.1 Dominating Options

The most conservative way to make this comparison is to look at whether there are any locations that dominate others in terms of both lower transmission danger and higher importance. By dominate, we mean that for a pair of location types one location is

[16] We omit "Bars and Clubs" as SafeGraph seems to dramatically undercount these locations. We omit "Parks and Playgrounds" as SafeGraph struggles to precisely define the borders of these irregularly shaped points of interest. We omit "Public and Private Schools" and "Child Care and Daycare Centers" due to challenges in adjusting for the fact that individuals under the age of 13 are not well tracked by SafeGraph.

superior to the other along all eight of our dimensions of risk and importance. This measure is conservative in the sense that any possible weighed aggregate measure of risk or importance will yield the same pairwise comparison.

Of our twenty-six categories, thirteen do not dominate nor are dominated by any other. Figure 1 reports the dominated/dominating pairs of categories for the thirteen remaining categories.[17]

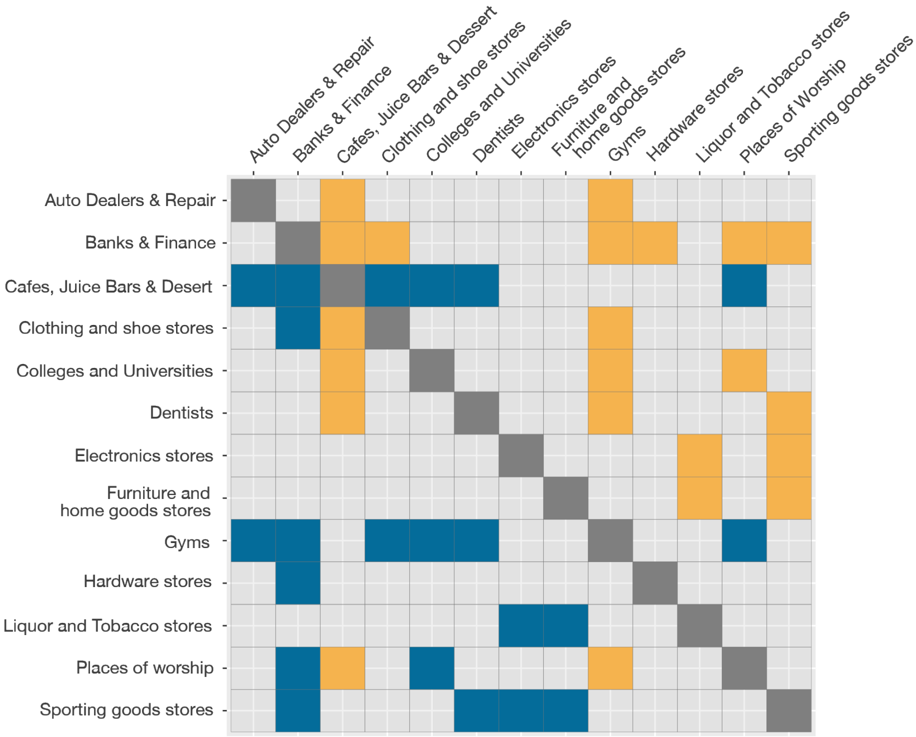

Figure 1: Grid indicating dominating and dominated categories. A cell is gold if the row category is better on all risk and importance dimensions than the column category. Blue for the converse.

Gyms and Cafes, Juice Bars and Dessert parlours are the two categories with the most dominated pairings. According to our measure, each of these locations should be opened only after banks, dentists, colleges, clothing stores, places of worship and auto dealers and repair shops. Within types of stores, we find electronics stores and furniture stores should be opened before liquor and tobacco stores and sporting goods stores. The location that comes out the best in this measure is banks and finance, which dominate six other categories.

[17]Note that the figure is mirrored, because if a Y-axis category dominates an X-axis category then the X-axis category is dominated by the Y-axis category.

3.2 Comparing Location Categories Using Composite Risk and Importance Indexes

Another way to determine which locations it makes sense to open first is to create overall indexes of danger and importance, and identify outliers. We create our danger index as the average rank of a category in the four danger measures. We create our importance index as the average rank of a category in our three economic importance and one consumer importance measure. We up-weight the consumer importance measure so that it is equally weighted with the three economic importance measures.

We perform this analysis separately for metro and non-metro areas. Non-metro areas constitute 15% of the population and 72% of the land area of the US. Note that transmission risk and consumer welfare rankings vary by metro/non-metro, but economic data does not.

Figure 2 reports the results of this analysis. There is a strong positive relationship between the danger of a location category and its importance. However, there are clear outliers. Those in the top left corner of both panels have relatively high importance but low danger. Categories near the bottom right corners of each panel have relatively high danger and low importance. Categories are colored from gold to blue as a function of their importance relative to danger. More precisely, we estimate a linear regression, including an intercept term, of importance index as a function of the danger index. Categories are colored by the magnitude and sign of the residual.

The metro and non-metro area index figures are remarkably similar, suggesting that the urban-rural divide is not a particularly important dimension for policymakers. Both figures agree that banks, general merchandise stores (i.e. Walmart), dentists, grocery stores, and colleges and universities should face relatively loose restrictions. They also agree that gyms, sporting goods stores, liquor and tobacco stores, and cafes should face relatively tight restrictions.

3.3 Changes in Visits from February to March

As mentioned above, there is a dramatic decrease in visits to all locations from February to March 2020. A natural final question is whether these reductions in visits are spread evenly across locations, or whether the reductions follow the risk-reward tradeoff we measure.

Figure 3 plots the percent decrease in visits to a location type, from February to March 2020 as a function of 'Importance-Risk Tradeoff Favorability'. Importance-Risk Tradeoff Favorability is the disproportionate importance of a category relative to it's risk (i.e. the gold to blue categorization in Figure 2, except aggregated for all regions). Categories on the right of the figure should face less restrictions according to our analysis and vice versa. The size of the points is proportional to total visits in February 2020.

As can be seen, weighing by initial visits, there is a clear positive relationship. This suggests that at least some of the cost-benefit analysis we measure is being internalized by US consumers, businesses, and policymakers. The two largest outliers

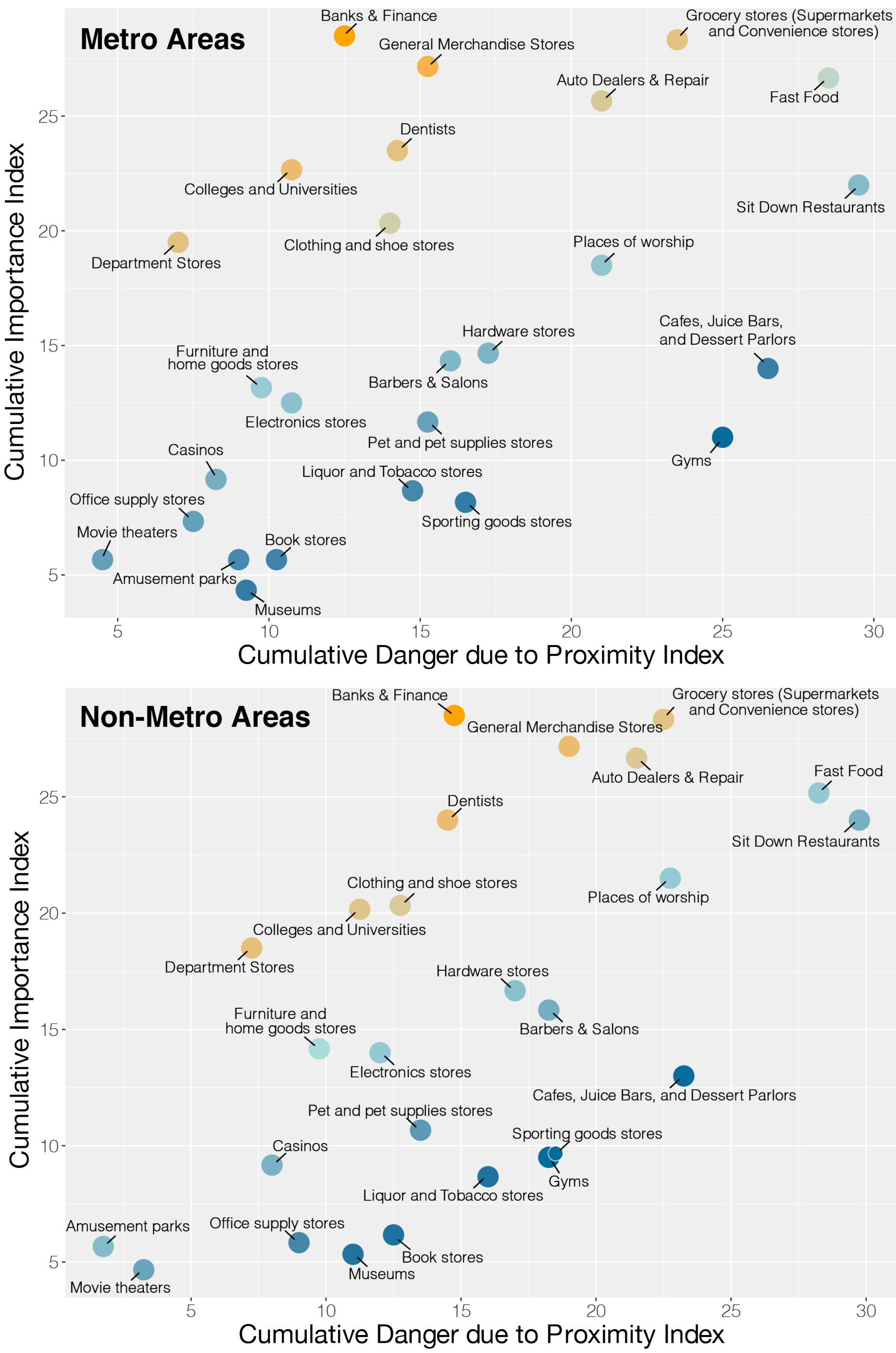

Figure 2: Category importance index and danger index for metro and non-metro areas. The color scale reflects the residuals by category of a linear regression of the importance index on the danger index. Golden categories have disproportionately high importance for their risk, blue categories have disproportionately low importance.

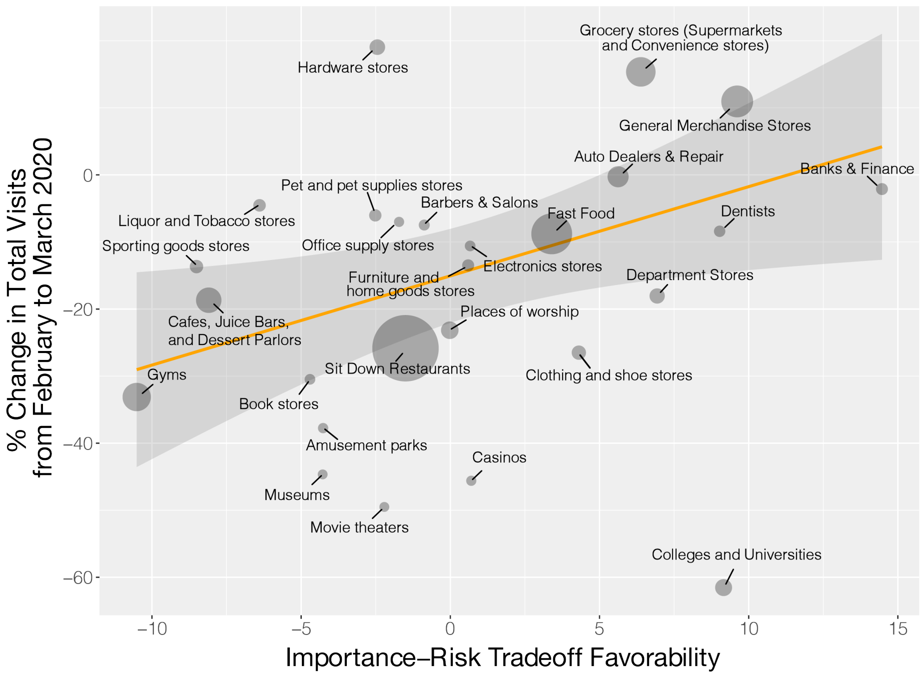

Figure 3: Change in location category visits versus the category importance/risk residual. Categories with higher residuals are positive outliers of a regression of importance residual on risk residuals and vice versa. The size of the points is proportional to total visits in Feburary 2020.

are colleges and universities, and hardware stores. We find colleges to be relatively good tradeoffs, but most have been shut down in March, leading to a 61% decline in visits. Conversely, liquor and tobacco stores we find to be relatively poor tradeoffs (due to mediocre economic importance and small busy stores) yet the number of visits to these locations has declined by less than 5%. Hardware stores are the location which have seen the largest increase in visits, as individuals scrounge for personal protective equipment and other home supplies.

It is important to note that these declines in attendance are due to a mix of federal government, state and local government, business, and individual level actions. We think that our tool can be useful for any actor looking to find smart ways to minimize COVID-19 transmission risk.

4 Discussion

Governments and civic organizations across the world have made different decisions about how to implement and relax social distancing measures. As they do so, they have various tools at their disposal. In the US, many of these restrictions have been specific to the type of location. The details of these restrictions have varied from state to state. For example, as of 4-18-20, Alabama has closed schools, day cares, gyms, movie theaters and other 'non-essential businesses'. On the other hand, Nebraska has not ordered closures of day cares, but has closed all liquor stores and religious gatherings. New Mexico also has let day cares operate, but have closed gun stores, liquor stores, and most religious gatherings.[18]

Why are different states adopting such different policies regarding which areas to shut down? One possibility is state-level variation in the importance or danger of locations. This variation would likely have to be separate from urban-rural heterogeneity, which we showed above to not make much of a difference.

We don't know much about how most states are deciding to prioritize closures and re-openings, but New York at least seems to conceptualize the problem the same way we do. On April 16, the governor of New York Andrew Cuomo, gave a press conference where he presented a slide with a two by two grid. The grid divided businesses conceptually into essential vs. non-essential and high-transmission risk vs. low-transmission risk categories. He declared that businesses that are essential and low risk should be opened first, but failed to list which types of locations belonged where in the grid (see supplementary figure S7). We hope that our analysis will help Governor Cuomo and others to populate their grids.

An alternative government strategy would be to target the danger of visiting certain locations directly. Mandatory mask wearing and 6-foot rules are doing some of this work. Some regions have also attempted to directly regulate the density of location visits. For example, Hesse (a state in Germany) has ordered all stores to stay below a density of one person per 20 square meters.[19] Enforcing social distancing within locations is an effective solution in theory but it is practically challenging. For example, Germany plans to open up smaller stores and keep larger stores closed since policymakers believe that it is easier to enforce social distancing rules in smaller stores.[20] Only opening smaller stores seems counterproductive if the goal is to minimize density.

One current decision needing to be made is whether to open up universities. Moreover, plans have also been announced to open up hair salons, car dealers, bookstores, universities and museums and for restaurants, cafes, day care centres and places of worship to remain closed.[21] Our evidence suggests universities and auto dealers should be opened before book stores, museums, hair salons and cafes.

Our analysis has several limitations, some of which we partially address here. One is the assumption of homogeneity in the type of visitors that frequent a location. The most important dimension of heterogeneity is in age. Older individuals are much more susceptible to serious and illness and death from COVID-19. We therefore recreate figure 2 for all areas but restricting attention to visits from those over age 65.[22] The

[18]State level COVID-19 policies from the "COVID-19 US state policy database" Raifman J, Nocka K, Jones D, Bor J, Lipson S, Jay J, and Chan P. available at www.tinyurl.com/statepolicies. Retrieved 4-18-20.

[19]What you need to know about plans for Germany's states to ease lockdown retrieved 4-17-20

[20]https://www.reuters.com/article/us-health-coronavirus-germany-retail-idUSKCN21Y1T3, retrieved 4-18-20

[21]e.g. Germany, Switzerland, Denmark, retrieved 4-18-20

[22]We estimate the number of visits from those over 65 to a location through the census tract of visitors, assuming that visits from older guests are proportionate to their share of the

results of this analysis are in supplementary figure S8. We find no large differences between the overall cumulative danger index, and the 65+ specific one.

Another limitation related to visitor heterogeneity is distance travelled to the location. For privacy reasons, SafeGraph does not provide the full breakdown of distance travelled. However, they do provide estimates of the median distance travelled by point of interest. Supplementary figure S9 reports the fixed effects associated with RUCC classification and location category in a regression of average median distance travelled in meters. We exclude this data from the main analysis because we believe it to be less reliable than the measures currently used in the danger index, because the average of medians is a strange object, and because much of the variation in median distance travelled is driven by RUCC classification rather than category. Supplementary figure S10 displays the sum across points of interest of the product of number of visitors and median distance travelled for the nine RUCC categories. Counties worse on this index might consider adopting stricter restrictions.

An additional supplementary figure, S12 directly incorporates information about old-age visits and visitor travel distance into our main analyses. Figure S12 replicates the analysis in 2 and 3 except with the four danger measures replaced by nine: four of these additional measures replicating our main danger measures but only for individuals 65 and older, and the final measure is weighted average median distance travelled to a location. The chart is plotted for all US regions. The analysis is essentially unchanged by these additions to the danger index.

A final limitation of our main analysis that we can address is heterogeneity in the danger of tasks performed in a location. We measure this heterogeneity through the share of occupations in an industry requiring high physical proximity.[23] Supplementary figure S11 reports this share by category, plotted against the risk-importance tradeoff residual, for two different proximity threshold. Using the very high threshold, only barbers and salons and dentists stick out as raising additional safety concerns. Using the moderately high threshold, movie theaters, gyms, amusement parks, and different types of restaurants do as well. We do not include this data in our main analysis because the need to be in close contact with visitors impacts both the risk of the category and the economic cost of shutting a location down. A category with a high share of workers who do not require close proximity has a workforce that would be better able to work from home.

Our analysis also has limitations that we cannot address as well. As noted above, one major limitation is our lack of any analysis of spillovers or linkages across locations types. This could take the form of importance linkages (one category provides an important input or complement to another) or visits to locations that are close

population. In calculating the old-person-hours of visits above a density threshold, we use visits from all guests in calculating location density.

[23]Occupation required physical proximity is measured through the O*NET physical proximity item: "To what extent does this job require the worker to perform job tasks in close physical proximity to other people?" Industry occupational employment is derived from the BLS OES May 2019 Release. The BLS OES does not provide detailed employment breakdowns for every six digit NAICs industry. For some categories, this means that we match to occupational employment mixes at a higher level of aggregation. Data retrieved 4-22-20.

substitutes or only enjoyed in combinations. Another is that our consumer welfare measures do not incorporate the possibility that a small subgroup of the population gets a disproportionate amount of benefit from a certain location. For example, places of worship might bring a lot of benefit for religious people. Moreover, our consumer welfare measures do not incorporate some of the externalities associated with keeping certain locations open. For example, gyms or churches might be essential for maintaining mental health in a way that is not fully accounted for in our consumer welfare measure. Future research can improve upon our danger and consumer welfare importance measures by incorporating additional data sources. In utilizing our indexes, policymakers should leaven our analysis with their own best judgement about unaccounted for risks and benefits of a category for their region.

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Supplementary Tables and Figures

Category Name	NAICS Codes	Total Visits Feb. 2020
Bars and nightclubs	722400	14294093
Museums	712110	16808639
Movie theaters	512131	17628164
Gambling locations (Casinos etc.)	713200, 721120	21185754
Office supply stores	453210	21536208
Amusement parks	713100	25807889
Book stores	451211	29160860
Electronics stores	443100	29506230
Barber shops and beauty salons	812100	34053753
Dentists	621200	40435359
Furniture and home goods stores	442100, 442200	49751106
Banks and other financial services	522100, 523900, 523100	49797490
Pet and pet supplies stores	453910	54236550
Liquor and Tobacco stores	445300, 453991	57252260
Sporting goods stores	451110	70550605
Clothing and shoe stores	448100, 448200	85232888
Department stores (e.g. Target)	452200	1.002e+08
Hardware stores	444130	1.041e+08
Child care and day care centers	624400	1.066e+08
Colleges and Universities	611300	1.251e+08
Places of worship	813100	1.365e+08
Automobile dealers & Auto repair	441100, 441300, 811100	1.892e+08
Parks and playgrounds	712190	2.241e+08
Cafes, Juice Bars, and Dessert	722515	2.523e+08
Gyms	713940	2.961e+08
Grocery stores (e.g. Supermarkets)	445100	3.140e+08
General Merchandise (e.g. Walmart)	452300	3.559e+08
Schools: K - 12	611100	4.391e+08
Limited restaurants (e.g. fast food)	722513	5.001e+08
Full service restaurants (sit down)	722511	8.847e+08

Table S1: List of categories and constitutive NAICS industries

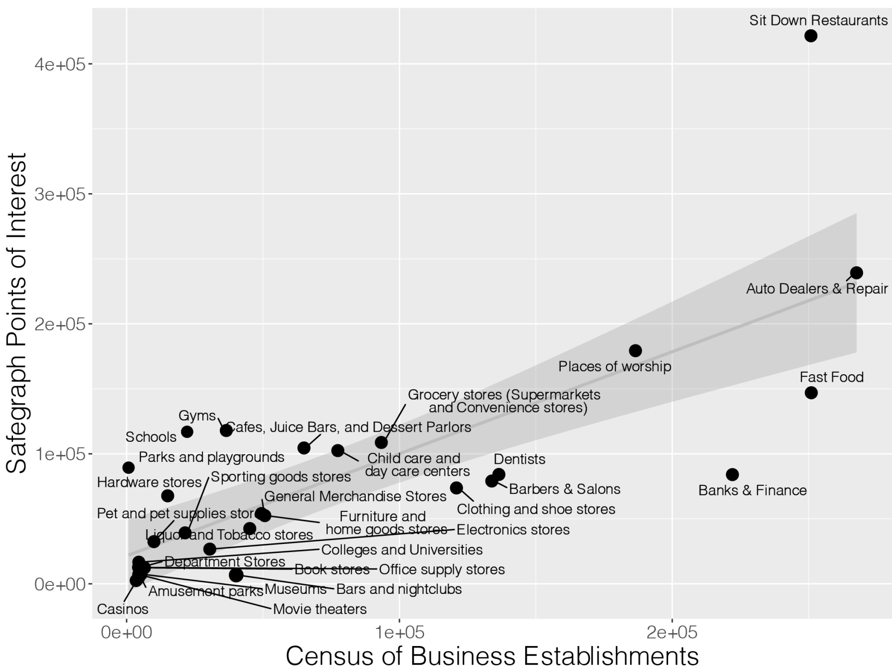

Figure S1: Number of establishments (Census Statistics of US Businesses) and Points of Interest (SafeGraph) for each of our thirty location types.

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.

We want to reward you for thinking carefully. Therefore, we will randomly pick one of you and give you **$200** in cash reward or gift card for your preferred location.

It is in your best interest to think carefully and choose your preferred location in each question.

Figure S2: Choice experiment instructions

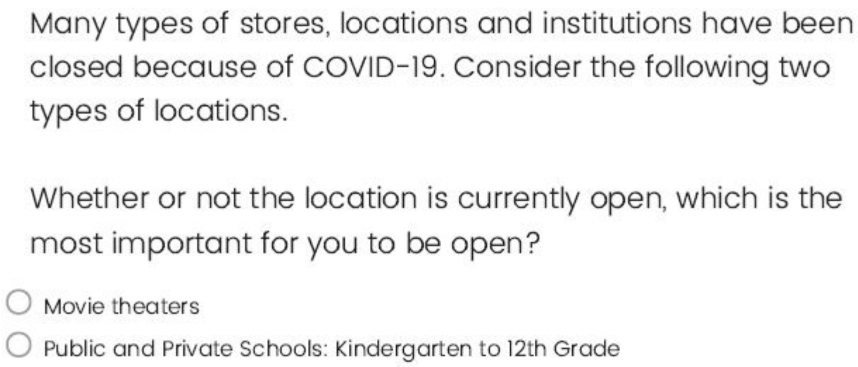

Figure S3: An example of a single binary discrete choice experiment

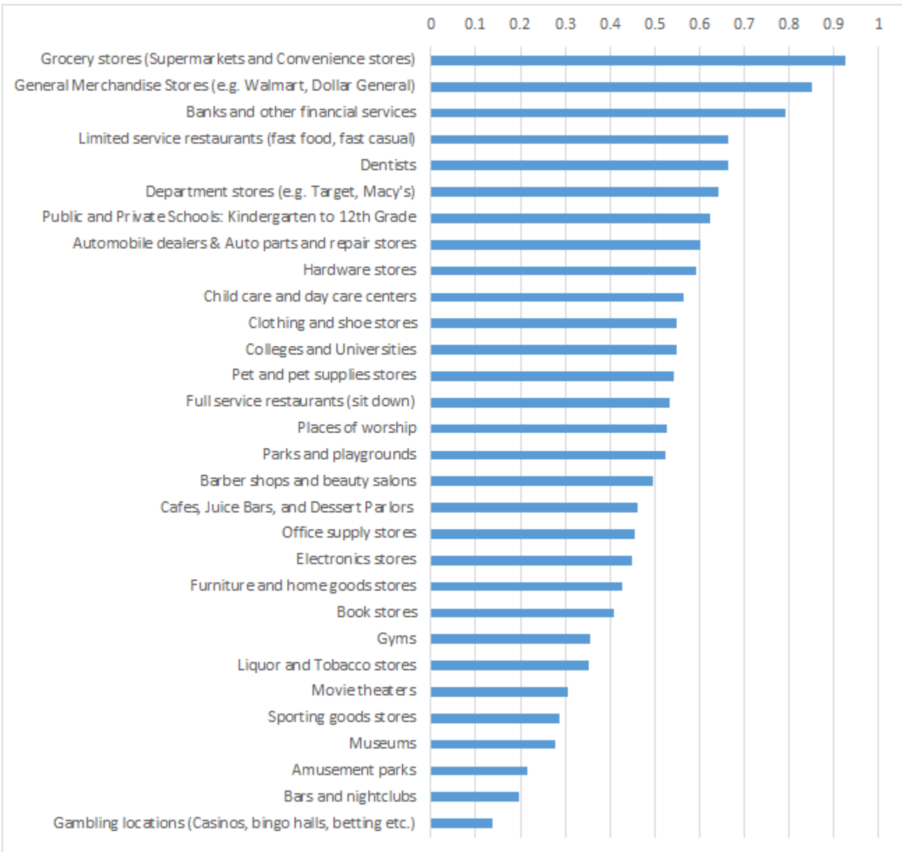

Figure S4: Ranking of categories based on their consumer welfare importance

Category Name	Difference in consumer welfare importance (Non-metro − Metro)
Places of worship	0.08
General Merchandise Stores (e.g. Walmart, Dollar General)	0.07
Electronics stores	0.06
Hardware stores	0.06
Automobile dealers & Auto parts and repair stores	0.05
Sporting goods stores	0.05
Full service restaurants (sit down)	0.05
Barber shops and beauty salons	0.03
Museums	0.03
Furniture and home goods stores	0.01
Banks and other financial services	0.01
Book stores	0.01
Dentists	0.01
Clothing and shoe stores	0.01
Public and Private Schools: Kindergarten to 12th Grade	0.01
Grocery stores (Supermarkets and Convenience stores)	0.01
Department stores (e.g. Target, Macy's)	-0.01
Bars and nightclubs	-0.02
Pet and pet supplies stores	-0.02
Child care and day care centers	-0.03
Limited service restaurants (fast food, fast casual)	-0.03
Amusement parks	-0.04
Gambling locations (Casinos, bingo halls, betting etc.)	-0.04
Cafes, Juice Bars, and Dessert Parlors	-0.05
Movie theaters	-0.05
Colleges and Universities	-0.05
Liquor and Tobacco stores	-0.05
Parks and playgrounds	-0.05
Office supply stores	-0.07
Gyms	-0.09

Table S2: Differences in consumer welfare importance (Non-metro − Metro)

Figure S5: Ranking of the different location categories by the Trasmissibility Risk. Top location categories are riskier. Also shown how the ranking changes between February 2020 (left) and March 2020 (right). The Risk metric used here is the number of person−hours of visits during crowding of more than 1 visitor per 113 square feet (a six-foot radius circle). The size of the circle is related to the log of the risk metric.

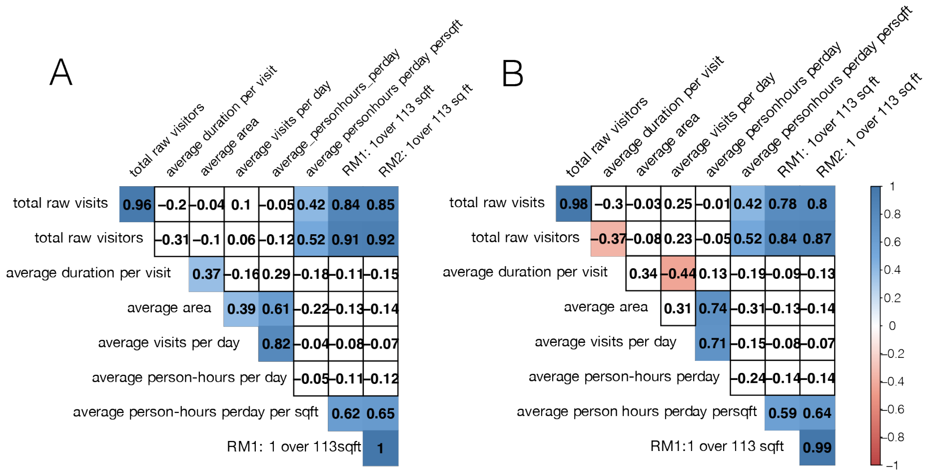

Figure S6: Correlation coefficients between different transmissibility risk measures in A. February 2020, B. March 2020. "RM1: 1 over 113 sq. ft." is referring to the Person-hours of visits during crowding of more than 1 visitor per 113 sq. ft. (i.e. sum over the hours that the number of person hours per day per sq. ft. is more than 1/113). This is the measure we use in the main analysis. "RM2: 1 over 113 sq. ft." is the person-hours of visits sum over the hours that the number of people per sq. ft. is more than 1/113.

Figure S7: Screencapture from NY Governor Andrew Cuomo's 4-16-20 press conference. Retrieved 4-18-20.

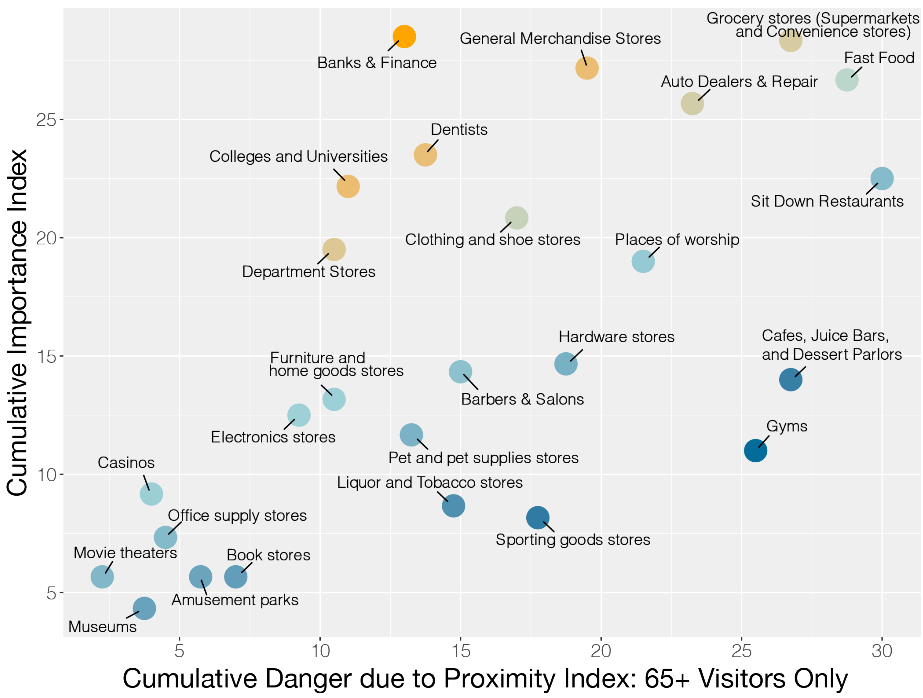

Figure S8: Category importance index and danger index, with danger index restricted to individuals 65 or over. The color scale reflects the residuals by category of a linear regression of the importance index on the danger index. Golden categories have disproportionately high importance for their risk, blue categories have disproportionately low importance.

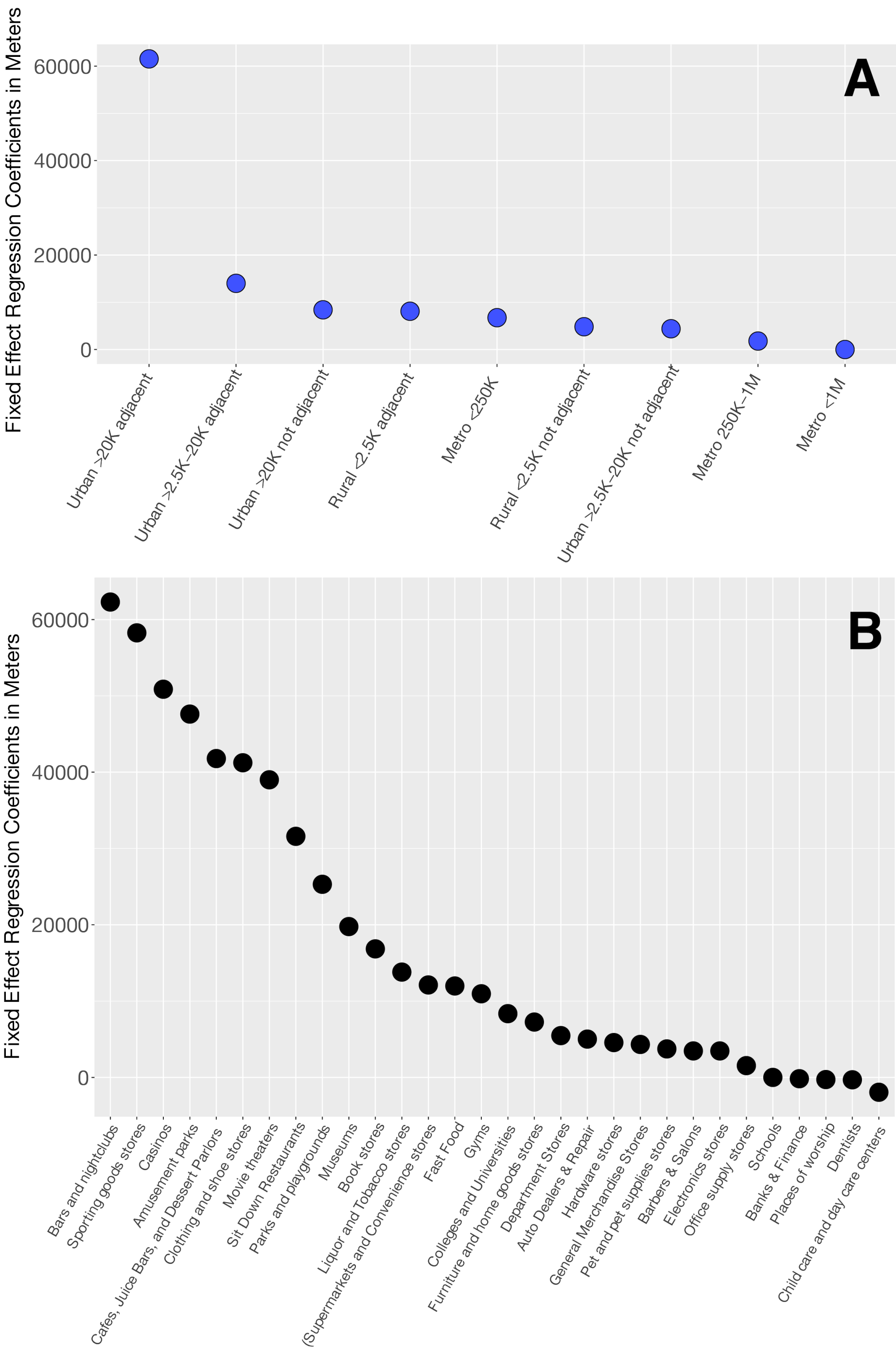

Figure S9: Fixed effect coefficients from a regression of median distance travelled in meters, averaged by category and RUCC classification, on these groupings. In each panel, one category is omitted and takes a coefficient value of 0.

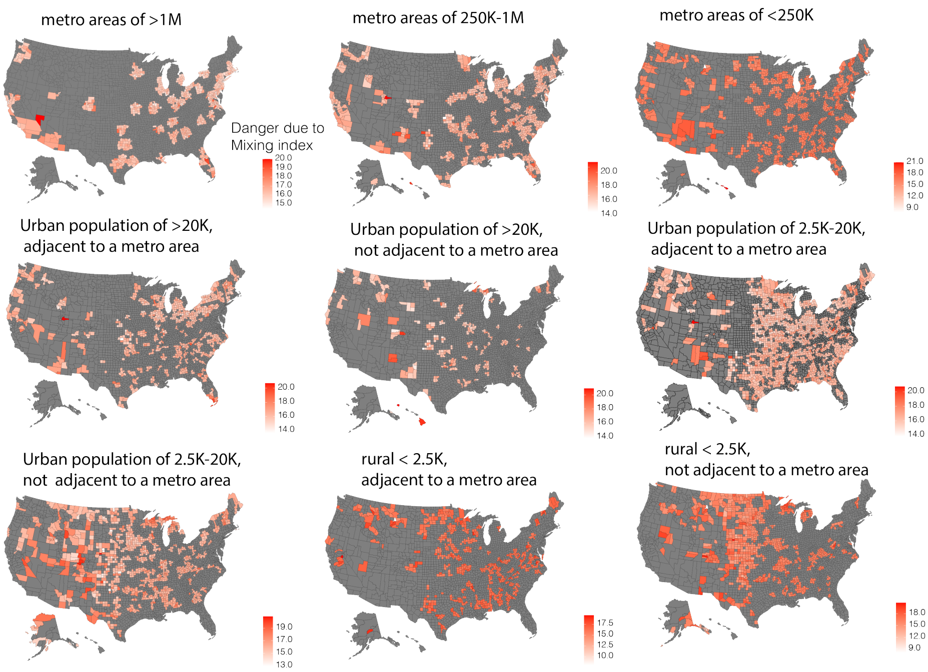

Figure S10: Weighted by the number of visitors index of distance travelled to a location by the county of the location's RUCC classification.

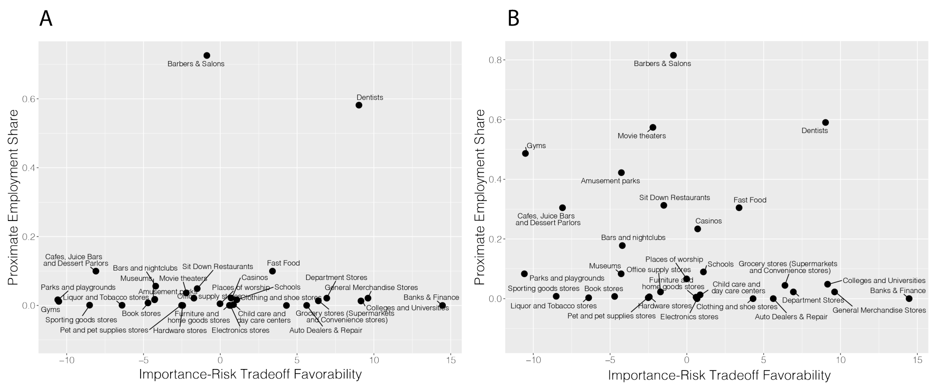

Figure S11: Share of employment by category requiring very high and moderately high physical proximity, plotted against the importance-risk tradeoff residual. Panel (A) uses a physical proximity score threshold of 90, and panel (B) uses a physical proximity score threshold of 80.

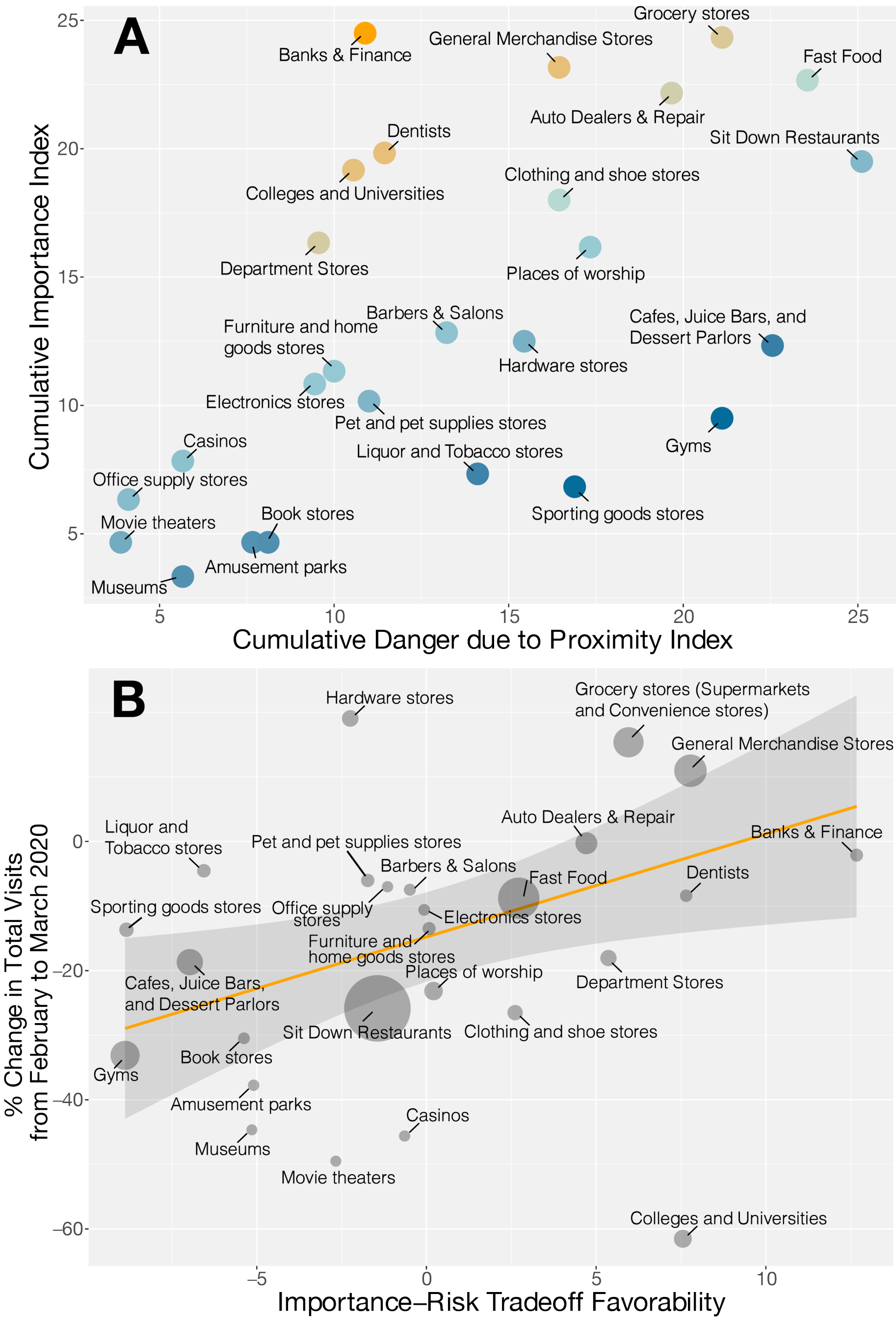

Figure S12: A. Category cumulative importance index and cumulative danger index. The color scale reflects the residuals by category of a linear regression of the importance index on the danger index. Golden categories have disproportionately high importance for their risk, blue categories have disproportionately low importance. B. Change in location category visits versus the category importance-risk residual. Marker sizes are proportional to total visits in February 2020.