The role of urban amenities in facilitating social mixing

Evidence from Stockholm

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Motivation

Ever since Jane Jacobs published her seminal works that championed the community-based approach to city building, urbanists and social scientists have worked to develop our understanding of how to build stronger and more equitable communities in cities. In 1982, building on the works of Jacobs, Ray Oldenburg published an article defending the role of informal gathering places – places like parks, hairdressers, and sidewalk cafes – as the foundation of a functioning civil society and democracy Oldenburg and Brissett (1982). He argued that cities need more "third places" outside of home and work, where people of different social classes can come together and interact in an unplanned way, fostering a sense of shared experience and trust.

More recent large-scale studies of social groups gathering in places like schools, workplaces, and churches also suggest that exposure to people from other socioeconomic classes plays an important role in bridging the social gap by improving the economic mobility of the poor (Chetty et al., 2022), correcting misperceptions about inequality and increasing support for progressive redistribution (Londoño Vélez, 2022). While the benefits of exposing people from different income groups to one another in various contexts are now widely discussed among scholars and policymakers, our tendency to cross paths with strangers has been in decline since the middle of the 20th century (Putnam, 2000; Klinenberg, 2018). This problem has only been exacerbated by the arrival of the COVID-19 era, which has increased rates of remote work and constrained people's recreational mobility spaces closer to home, making Oldenburg's ideas all the more relevant (Conti, 2022).

However, the impact of improving access to various urban amenities on one's daily exposure to diversity has not been previously systematically examined using quantitative causal inference methods. The extent to which people are segregated in these informal interactions is still an open question and a more difficult one to study, requiring comprehensive information on the ways that people move around cities on a daily basis. This, in turn, limits the ability of urban planners to develop evidence-based strategies to improve experienced diversity through design and policy.

There is a rich history of urban planning literature that explores these questions from qualitative perspective, highlighting social institutions such as libraries, grade schools, parks and religious organizations as critical urban infrastructure for social mixing (Nyden, Maly and Lukehart, 1997; Nyden et al., 1998; Peters, 2010; Peters, Elands and Buijs, 2010; Klinenberg, 2018; Legeby, 2013). As our technologies become more sophisticated and ubiquitous, new sources of big data allow us to massively scale up these qualitative and observational studies and test their hypotheses in a statistically rigorous way.

We use mobile phone data tracing 1.5 million devices to quantify how different types of gathering places contribute to improving the exposure to economic diversity at the individual level in Stockholm, Sweden. We first provide a descriptive analysis of places that appear to attract income-mixed populations and estimate correlations between the income diversity of individuals visiting a given part of the city and the types of amenities located there. Then, we employ causal inference methods to compare the relative contributions of these different amenities to experienced diversity.

To capture the co-location of individuals on a fine spatial and temporal scale and measure the extent to which urban residents are exposed to different social groups on a daily basis, we build on the recently developed methodologies that use human mobility traces from sources like mobile phone records, GPS records, and social media to quantify what we term *experienced income diversity* (Athey et al., 2021; Xu et al., 2019; Phillips et al., 2021; Wang et al., 2018; Davis et al., 2019; Moro et al., 2021). We use a mobile phone record dataset that was collected over the course of eight months between 2019 and 2021 and consists of millions of data points, each containing a unique, anonymized user identification, timestamp, and location approximated from the coverage area of the closest cell tower. To map the distribution of urban amenities, we combine data from OpenSteetMap with data provided by the City of Stockholm. For more details on data see the Methods section.

We compute the income mixing of visitors to each of the 500x500m grid cells that cover the entire city of Stockholm. Our measure, which we call the Experienced Diversity Index (ED), is equivalent to the duration-weighted average socioeconomic distance between individuals located in a given cell at a given time (see Xu et al. (2019) for the derivation of this measure). To predict individuals' income groups, we estimate each user's residence using their nighttime locations and assign the spatial area-weighted average income to each home grid cell using neighborhood income data from Statistics Sweden.

Results

Panel A of Figure 1 shows daytime experienced diversity across locations in Stockholm. This measure represents the average income difference between individuals gathered in a given grid cell at noon on a weekend day; low values indicate low income difference and thus low levels of experienced diversity in that grid cell and high values indicate high levels of experienced diversity (see Equation 1). We find that ED is highly clustered in space. For example, there are hotspots of high segregation for visitors in the far-north neighborhood of Kista and in the southern suburb of Tallkrogen. The wide neighborhood-to-neighborhood variation suggests that access to places with high social diversity is highly unequal in Stockholm. Panel B of Figure 1 shows differences in average experienced diversity by places of residence. This value represents the experienced diversity of people who live in a given grid cell, wherever they happen to be in the city at noon on a weekend day (see Equation 2). We see that the two measures are spatially correlated—individuals living in places where diverse groups of people gather also experience higher overall social mixing over the course of a day. This is natural, as people spend a significant amount of time in their home grid cell. That being said, there are some notable differences between the two maps. For example, the island of Södermalm (highlighted in yellow on the maps in Figure 1) exhibits relatively low location-based diversity (Panel A), indicating that the people who gather there are not very income-diverse; however, the same area exhibits relatively high residence-based diversity (Panel B), indicating that the individuals who live there encounter diverse groups of people as they move throughout their days.

The clear variation in location-based experienced diversity spurs a natural next question: what exactly is going on in areas with high experienced diversity? We use Beta regression to estimate the relationship between the presence of various types of urban amenities (see Figure 2) and experienced socioeconomic diversity in a given location. As our variable of interest, we specifically focus on the experienced diversity of daytime visitors in order to tease apart residential segregation from diversity experienced in public life outside of home. We estimate separate models for weekend and weekday experienced diversity, as factors affecting travel patterns are fundamentally different during weekdays compared to weekends. We also include an eigenvector spatial filter (ESF), which captures spatial dependencies within our model and eliminates residual spatial autocorrelation

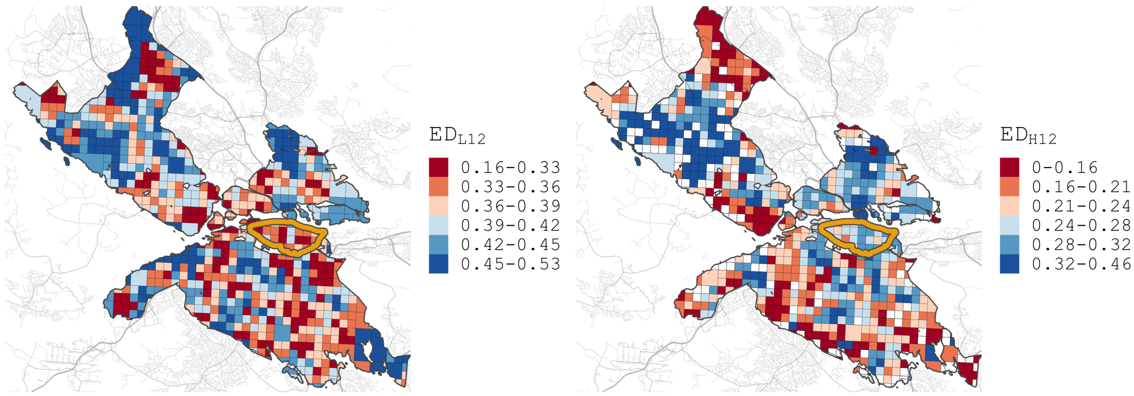
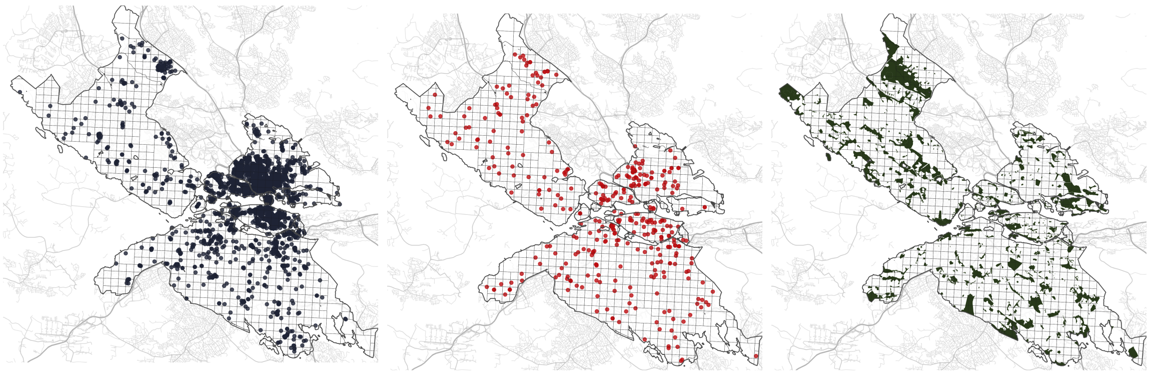


FIGURE 1: **Experienced diversity by destination and origin home location**. Panel A shows the experienced diversity of visitors to each grid cell at noon on a weekday. Red cells (low values) represent more segregated spaces. Panel B shows the average experienced diversity at noon on a weekday by residence location, averaged across all locations that residents of a given home grid cell may be visiting. Red cells (low values) represent more segregated individuals.

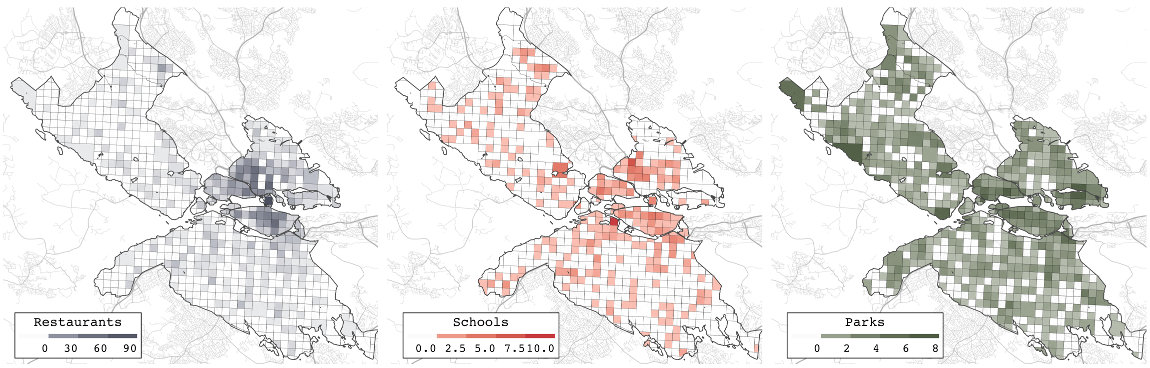
Tiefelsdorf and Griffith (2007).

Figure 2 shows the estimated coefficients in our regression model. We find that during daytime, weekend hours people are most exposed to economic diversity when located in areas with relatively more libraries, educational institutions, healthcare facilities, and restaurants. Specifically, one standard deviation increase in total number of restaurants is associated with a 1.29-standard deviation increase in experienced diversity, controlling for presence of other amenities and unobserved spatial covariates. The effect size is .78, .57, and .34 standard deviations for healthcare facilities, schools, and libraries, respectively. These relationships shrink slightly in magnitude but remain significant during weekday hours for educational institutions and libraries, indicating that these spaces host more income-diverse encounters even during non-leisure hours.

The least income-diverse locations are those that include many bars and grocery stores. Areas with one standard deviation more total bars and total grocery stores are associated with .61 and .38 standard deviations lower experienced diversity, respectively, controlling for presence of other amenities and unobserved spatial covariates. However, these relationships do not hold during the weekdays, indicating that areas with many bars and grocery stores host less-diverse social interactions than other areas specifically during leisure hours.



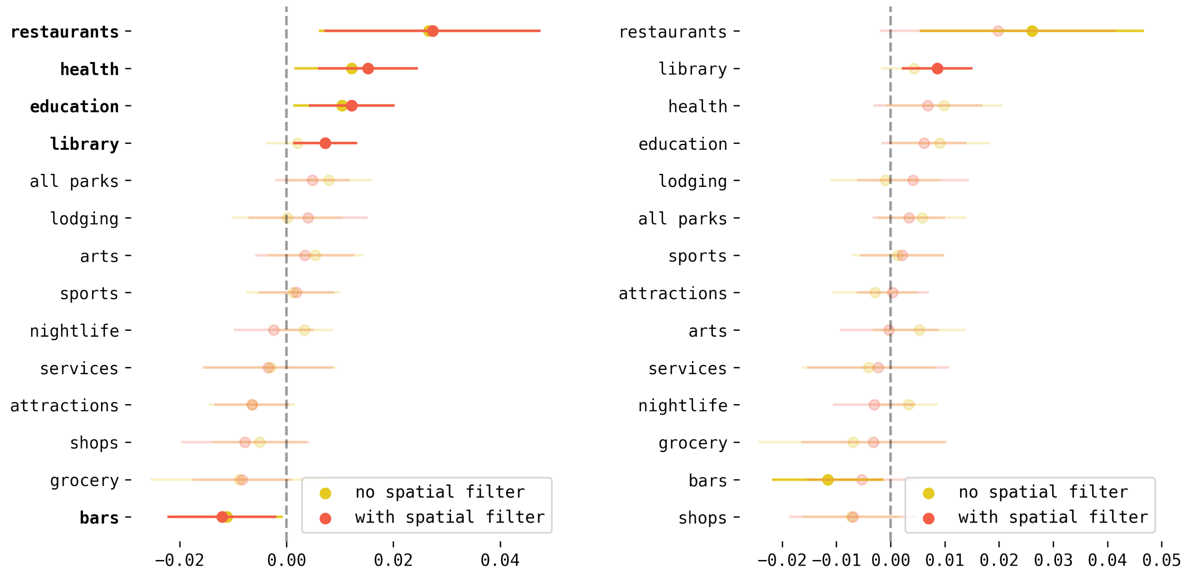
(a) Restaurant locations. (b) School locations. (c) Park locations.



(d) Grid cell restaurant counts. (e) Grid cell school counts. (f) Grid cell park counts.

FIGURE 2: Amenity locations (top row) and grid-cell-level counts (bottom row) for three example amenity categories: restaurants, schools, and parks. Data for restaurant locations is obtained from OpenStreetMap (OSM), while data for park extents and school locations is obtained from Stockholm Open Data Portal. Park counts represent the total count of parks intersecting a given grid cell.

However, the estimates presented in Figure 2 are not causal and should not be interpreted prescriptively. While the regression results imply that more income-diverse groups of people gather in and around areas with more libraries, schools, healthcare facilities, and restaurants, they do not necessarily imply that providing more of those types of spaces will foster more experienced diversity. First, it does not account for unobserved local factors, like crime activity, which may impact both the diversity of its visitors and the presence of certain amenities. Second, we can not exclude the possibility that unobserved individual characteristics such as race, ethnicity, or family status, matter both for personal preference for certain amenities – like libraries – and for the propensity to travel to places that are income-diverse. Thus, while our place-level analysis characterizes locations



(a) **Weekend integration coefficients.** (b) **Weekday integration coefficients.**

FIGURE 3: Regression coefficients representing the relationship between total count of a given amenity type in a grid cell and experienced diversity in that grid cell. The value for amenity type m is analogous to β_m in Equation 3 in the Methods section. Orange datapoints represent coefficient estimates in the model specification that includes an eigenvector spatial filter in order to account for spatial autocorrelation ("with spatial filter"); yellow datapoints represent coefficient estimates in the model specification that does not ("no spatial filter").

that are well-mixed socially, it does not tell us how the tools of urban policy and design can be employed to induce people to visit such places.

To assess causal effects of urban interventions on social mixing, we employ quasi-experimental data on temporary road closures, which allow us to identify the causal impacts of improving road access to several specific categories of amenities using a two-way fixed effect model. We use data on road closures to estimate changes in experienced travel times across the city (see Figure **??**). We quantify temporal variations in travel times to various urban amenities across Stockholm for a given user and calculate an aggregate access statistic, which we call *amenity access*, that represents a travel-time-weighted number of amenities of each category that can be accessed from the users' home location at a given point in time. The relative preference across similar places at different distances is modeled as a time-decay function with a factor of -0.18, corresponding to the elasticity of travel demand for leisure amenities with respect to travel time (from Redding, 2018; see Methods for details).

To draw the causal link between the travel accessibility of urban amenities and experienced

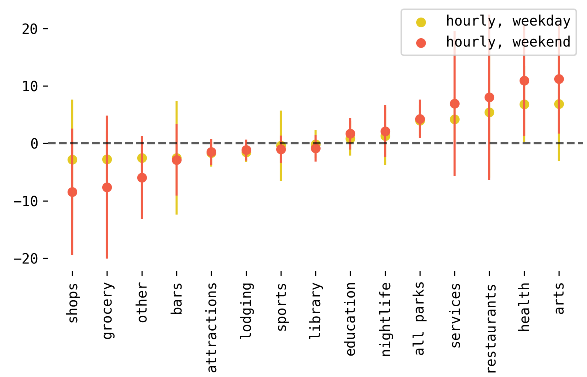
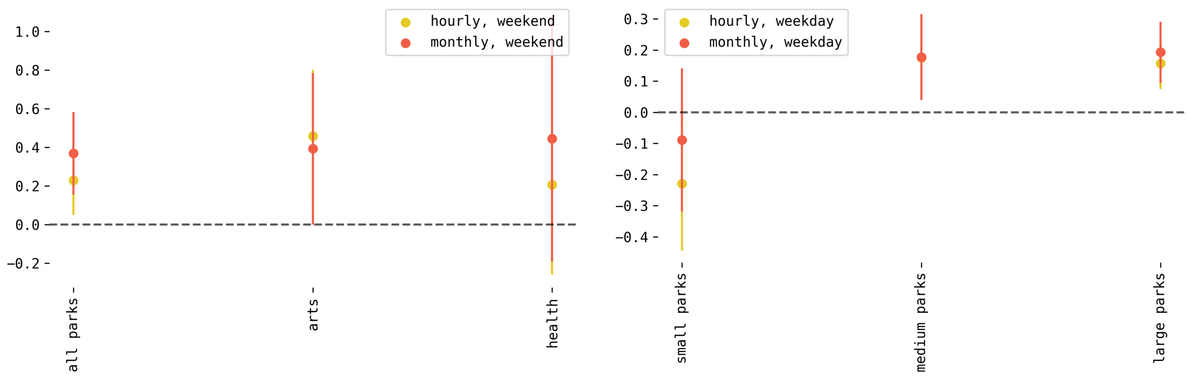


FIGURE 4: **Effect of travel time on visits to urban amenities.** Regression coefficients representing the relationship between access to a given amenity type and trips taken to that amenity type. The value for amenity type m represents the coefficient on access to amenity type m in the beta regression where the dependent variable is trips to amenity type m and the explanatory variables are access to all amenity types (β_m in Eq. 5 in the Methods section).

diversity we first verify that higher travel times, as captured by our access metric, indeed divert people from visiting certain destinations of interest. We investigate the link between our measure of access and visits to corresponding amenities using a two-way fixed effects model. Figure 3 shows the results of estimating a regression model describing the relationship between our measure of access to a given amenity type and trips taken to areas housing that amenity type (see Methods for details). When residents experience a temporary increase in travel times to parks, arts and cultural institutions, and healthcare establishments, they end up also significantly less likely to visit those places. This relationship is statistically significant for parks during both weekday and weekend hours, and arts and cultural institutions and healthcare establishments during weekend hours only.

Given that fluctuations in travel time-based access have a significant effect on volume of travel to parks, arts and culture institutions, and healthcare facilities, we can measure the causal effect of access to these three amenity categories on experienced diversity. While we find quantitatively large effects of our access measure for restaurants and services on trips, our margins of error do not allow us to use them to capture the causal links between visits and experienced diversity.

We quantify the hypothetical impact of reducing travel times to parks, arts and culture institutions, and healthcare facilities on experienced income diversity at the individual level using a two-way fixed effects model. Our approach relies on the assumption that travel time variations due to road closures faced by each individual over time are not correlated with the unobserved temporal shocks that affect the social integration of that individual, conditional on the covariates



(a) Effect of amenity access of experienced diversity.

(b) Effects of parks broken down by size.

Figure 5: In panel (a), values represent the effect of increased access to the given amenity type from a grid cell on experienced diversity of that grid cell's residence. Panel (b) suggests that the positive effect of parks on experienced diversity is mainly driven by medium- and large-sized parks.

capturing access to different types of amenities in our sample. Location fixed effects are used to alleviate the concerns about static place-level characteristics affecting people's propensity to socialize – like the presence of employment – and thus confounding the estimates. Time fixed effects for each combination of month, weekend, and hour-of-day observations are included as well to account for the possibility that road closures were more likely to happen at certain times of the year or in certain places where experienced integration has specific temporal trends. For example, they allow us to account for the fact that during the summertime road closures may be more frequent and experienced integration may be higher in certain places. Since in many cases different urban amenities tend to co-locate (e.g. parks and schools), the presence of unobserved amenities also presents a challenge for our causal analysis. Hence, we include all amenity categories available to us in our regressions.

We find that Stockholm's residents experience significantly less face-to-face encounters with people of different income groups as a consequence of temporarily experiencing longer travel times to parks and arts and culture institutions on weekends. Panel (a) of Figure 6 shows estimates of our two-way fixed effects model explaining temporal changes in experienced diversity using our measures of travel-time accessibility to these amenities. One standard deviation increase in access to parks results in a .36-unit increase in experienced diversity on weekend days. To put this into context, the average deviation from mean park access within a grid cell due to road closure is associated with a drop in experienced diversity of 0.78 standard deviations. When we break down parks into three quantiles by size, it becomes clear that this effect is driven primarily by medium- and large-sized parks—the effect of small parks is actually negative (though imprecisely estimated), as seen in Panel (b) of Figure 6. Arts institutions also have a positive effect: one standard deviation increase in access to arts and culture establishments results in a .39-unit increase in experienced diversity for the users in our sample. The average deviation from mean arts access is associated with a 0.55-standard deviation drop in experienced diversity.

Discussion

This study presents new perspectives on analyzing social mixing and socioeconomic integration in cities. As dynamic, mobility-based segregation and integration are beginning to be mapped and measured using large, geospatial datasets, there is ample opportunity to explore what the implications of these measurements are for the design of inclusive and well-connected cities. We highlight the potential of specific types of amenities to foster diverse social interactions.

Our results provide important evidence that certain types of urban spaces host interactions between more income-diverse groups of Stockholm residents; namely, areas of the city with more libraries, educational instutions, healthcare establishments, and restaurants host more exposures between people who are different from one another in terms of income than areas with otherwise-similar amenity distributions. Further, we identify a causal relationship between parks and arts and culture establishments and experienced diversity: temporary, random decreases in access to these spaces due to road closures result in less-diverse encounters for urban residents.

That being said, a major limitation of this work is that our experienced diversity index measures the co-presence of individuals from diverse income groups—in other words, the potential of establishing meaningful social interactions across different groups. However, it is not able to capture actual interactions between people; just because two people are located in the same space doesn't necessarily mean that they are interacting with one another. While previous work has shown that diversity of co-presence is a good indicator of diversity of social relationships (Xu et al., 2019), future work quantifying the relationship between co-presence and meaningful interactions or the formation of social relationships would add nuance to the results presented here.

There are many other open questions in this space for future research. While we have identified a relationship between experienced integration and a few specific types of policies and spaces, others remain unexplored; for example, how do mobility contraints imposed by road and transit networks impact experienced integration? How do land-use configuration and street morphology play into experienced integration? Further, how does context such as position in the road network or proximity to residential groups factor into the integrating effect of places like schools and parks? As urban income inequality grows and cities become more and more sprawling, these questions are critical to designing socially sustainable cities where resources are distributed equitably across all residents.

Methods

Mobile phone data

The mobile phone record dataset that we analyze consists of millions of datapoints collected over the course of eight months between 2019 and 2021, each consisting of a user id, a timestamp, and a cell phone tower id indicating the coverage zone in which the user is located. Together, this information provides a trace of users' movements throughout the city. We compute a measure that is equivalent to the duration-weighted average socioeconomic distance between individuals located in a given 500m $\times$ 500m grid cell of Stockholm at a given time, which we call the Experienced Diversity Index (ED)—see Xu et al. (2019) for a full description of this measure. We then use this index of integration to study the relationship between the presence of certain amenities in a given part of Stockholm and the diversity of residents gathered in that area.

Experienced Diversity

In order to calculate our experienced diversity measure (ED), we must first estimate the socioeconomic characteristics of the cell phone users in our dataset. We use the following procedure:

1. Divide the city of Stockholm into a 500m $\times$ 500m grid.
2. Calculate a characteristic income for each grid cell by taking the weighted average of median incomes of the DeSO areas with which the grid cell overlaps, where weights are area of overlap.
3. Estimate a home grid cell for each user based on the location that they spend the most amount of time at night (between 8pm and 7am) over the course of our study period.
4. Assign each user the characteristic income of their home grid cell.

Using this information, we are able to calculate a measure of the diversity of users gathered in a given grid cell at a given time. We use a diversity index which is equivalent to the weighted average socioeconomic difference between visitors to a grid cell, as defined by the formula below for individuals from grid cell i who are in location L at time T:

$$\text{Experienced Diversity(ED)}_{i,L,T} = \frac{\sum_{k_j} p_{k_j,L,T} \cdot s_{k_i \to k_j}}{\sum_{k_j} p_{k_j,L,T}},$$

where $p_{k_j,L,T}$ is the number of people of income k_j who visit L at time T, and $s_{k_i \to k_j}$ is a social distance measure between people of incomes k_i and k_j described in the Methods section of Xu et al. (2019). After diversity of exposures of an individual x in location L at time T is calculated, $ED_{x,L,T}$, we can aggregate up to the diversity of individuals gathered in a given L at T, $ED_{L,T}$ or the diversity of encounters by individuals with home location H at time T, $ED_{H,T}$ as follows:

$$\mathrm{ED}_{L,T} = \frac{\sum_{j \in \text{grid cells}} \mathrm{ED}_{j,L,T} \cdot p_{j,L,T}}{\sum_{j \in \text{grid cells}} p_{j,L,T}} \tag{1}$$

$$\mathrm{ED}_{h,T} = \frac{\sum_{L \in \text{grid cells}} \mathrm{ED}_{h,L,T} \cdot p_{h,L,T}}{\sum_{L \in \text{grid cells}} p_{h,L,T}} \tag{2}$$

We will use $ED_{L,T}$ in part one of this study, analyzing the diversity of individuals gathered around different amenities, and we will use $ED_{h,T}$ in part two of this study, analyzing the impact of access to different amenity types from one's home location on their experienced segregation.

Amenities data

Our primary dataset of amenity locations is scraped from OpenStreetMap (OSM), a comprehensive, collaborative mapping platform which contains crowdsourced information on the locations of points of interest such as restaurants, museums, post offices and bars across the city of Stockholm. OSM data has been found to be geographically precise. Previous quality evaluations have also shown that dense urban centers like Stockholm are in general more complete than other areas and that Sweden has a high completeness rate Barrington-Leigh and Millard-Ball (2017); Hochmair, Juhász and Cvetojevic (2018). In comparing OSM points of interest to a similar dataset put together by Statistics Sweden, we find strong correlations across the categories of clothing stores, grocery stores, restaurants, home and leisure stores, and services, further validating accuracy and completeness of the OSM dataset . We use the OSM dataset over the Statistics Sweden dataset due to its more detailed categories, which allow us to control for variation across more types of urban spaces.

We combine OSM data with two datasets from the city of Stockholm's open data portal. The first is Stockholm's 2022 sociotope map, which delineates "publicly accessible parks, natural areas, or other unbuilt areas where it feels nice to be." Specifically, we use the subset of these areas that are tagged as parks in order to supplement the parks data scraped from OSM. Because parks are often much larger than other buildings or amenities, and because they can vary greatly in size, the geographic extent information provided by the sociotope map provides valuable information about variation in access to parks across Stockholm that is absent from OSM's point-location data and allows us to distinguish between small neighborhood parks and large parks that draw people from across the city. We also utilize Stockholm's database of school locations, which we find to be more complete than OpenStreetMap's, and which labels schools by type (public/private and primary/secondary), allowing for a more detailed analysis of social mixing in proximity to schoools. The locations and grid-cell-level counts of parks, schools, and restaurants are illustrated in Figure 2.

Beta regression

The regression model assumes that experienced diversity for any grid cell k, y_k, is drawn from a Beta distribution with mean μ_t and precision ϕ, where:

$$g(\mu_{k,t}) = \sum_{m \in \text{amenity types}} \text{count}_k(m)\beta_m + \sum_{j=1}^{J} \lambda_j \tau_j + \alpha_{m(i)} + \theta_{y(i)} + \gamma_{h(i)}, \tag{3}$$

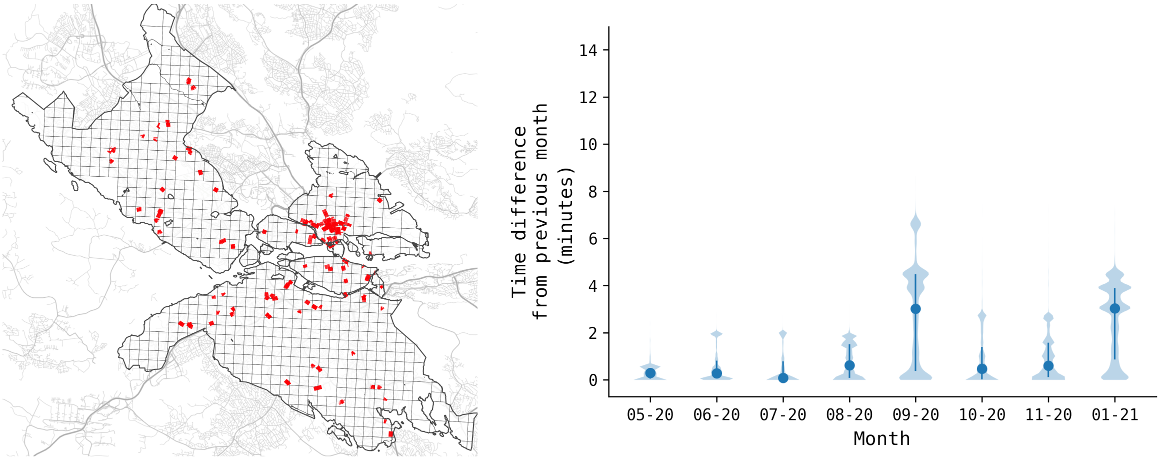
$$\text{for } g^{-1}(x) = \frac{e^x}{(1+e^x)}. \tag{4}$$

Here, $x_{k,m}$ is the number of amenity type m located in grid cell k and $\alpha_{m(i)}$, $\theta_{y(i)}$, and $\gamma_{h(i)}$ are monthly, yearly, and hourly fixed effects, respectively. The vectors τ are an eigenvector spatial filter which accounts for unobserved, spatially correlated confounders of experienced diversity and corrects for spatially autocorrelated errors (Tiefelsdorf and Griffith, 2007; Thayn and Simanis, 2013).

Causal inference

When roads close due to construction projects, travel times between various points in the city increase, making amenities more difficult to access for select populations in a way that we assume is uncorrelated with unobserved individual preferences and behaviors.

We obtain the full Stockholm street network and all mapped points of interest (POIs) from OpenStreetMap (OSM), an open source online mapping platform. We combine this information with data on road closures and construction projects from the city of Stockholm by creating separate versions of the road network for each month of our study period where we have manually removed street segments that are closed or limited-access during the given month. We calculate travel times



(a) Road closures over the course of the study period.

(b) Distribution of origin-destination travel time differences from the previous month.

FIGURE 6: In panel (a), values represent the effect of increased access to the given amenity type from a grid cell on experienced diversity of that grid cell's residence. Panel (b) suggests that the positive effect of parks on experienced diversity is mainly driven by medium- and large-sized parks.

between each pair of our 500m $\times$ 500m grid cells in Stockholm on these monthly road networks using the OpenRouteService (ORS) API, resulting in a panel of travel times between each origin and destination in our dataset.

Using these travel times, we calculate access to amenity type k for grid cell i at time t as follows:

$$\text{access}_{it}(m) = \sum_{j \in \text{grid}} \text{count}_j(m) \cdot \exp\{-\phi \cdot T_{ij}^{car}\},$$

where $\text{count}_j(m)$ is the total count of amenity m located in grid cell j, T_{ij}^{car} is the travel time between grid cells i and j by car, and ϕ represents elasticity of travel to travel time. We take $\phi = 0.018$, the value of leisure travel cost elasticity estimated in Miyauchi, Nakajima and Redding (2021). We then estimate the effect of changes in access to a specific amenity type on trips to that amenity type as described in the following equation:

$$\log \text{travel volume}_{imt} = \beta_m \text{access}_i(m) + \sum_{k \in \text{amenity types}} \beta_k \text{access}_i(k) + \mu_t + \nu_i + \epsilon_{imt}, \tag{5}$$

$$\text{travel volume}_{imt} = \sum_{j \in \text{grid cells}} \text{trips}_{ij} * \text{count}_j(k) \tag{6}$$

where $\text{travel volume}_{imt}$ is the volume of trips to locations with amenity type m at time t from cell phone users whose home locations are estimated to be in grid cell i, μ_t are monthly fixed effects, ν_{ij} are origin-destination pair fixed effects, and ϵ_{ijt} is an error term.

We then estimate the effect of access to different types of amenities on experienced integration as follows:

$$ED_{i,H,T} = \sum_{k \in \mathcal{K}} \beta_k access_{it}(k) + \mu_i + \nu_t + \epsilon_{it},$$

where $ED_{i,H,T}$ is the level of diversity experienced over time t by the individuals living in grid cell i, μ_i are grid cell fixed effects, ν_t are monthly fixed effects, and ϵ_{it} is an error term. Here, for a given grid cell i, all variation in our access variable is due to road closures. The findings from this regression are reported in Table **??**.

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