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Research Paper

The role of urban amenities in facilitating social mixing: Evidence from Stockholm

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HIGHLIGHTS

- Using mobility data, we measure income diversity of urban encounters in Stockholm.
- More diverse groups of people gather around restaurants, libraries, and schools.
- Increased access to parks and services results in decreased social segregation.

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ABSTRACT

Though the existence of socioeconomic segregation in social interactions has been consistently documented and compared across cities in a growing body of literature, less attention has been paid to within-city analysis of the types of places at which particularly integrated or segregated interactions occur. Dependencies between socioeconomic profile, residential location, preferences and behavior make this kind of analysis difficult. Further, beyond understanding where diverse social interactions take place, it is important to know whether increasing access to those types of spaces via changes to the transportation network can actually increase the level of diversity in social interactions—a more causal question that remains relatively unexplored in the literature. This study presents new perspectives on analyzing social mixing and socioeconomic integration in cities using geolocated cellphone data. Using a call detail record dataset which describes the movements of over one million cell phone users in Stockholm, Sweden, this study quantifies the contribution of access to various types of urban amenities to one's exposure to people with diverse income levels. Our results provide evidence that areas of the city with more libraries, educational institutions, healthcare establishments, parks and restaurants host more exposures between people who are different from one another in terms of income. Further, we leverage random shocks to the transportation network that come from maintenance-based road closures to identify a causal relationship between access to parks, services and healthcare establishments and experienced income diversity. Temporary, random increases in travel times to these spaces due to road closures result in less diverse day-to-day encounters for urban residents.

1. Introduction

Recent large-scale studies of social groups gathering in places like schools, workplaces, and churches have highlighted the importance of intermingling between people from different social and economic backgrounds in 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 exposure beteween people from different income groups in various contexts are now widely discussed among scholars and policymakers, our likelihood of crossing 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 (Conti 2022, Legeby et al. 2023).

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While our increasing tendency to self-segregate by race and income in our daily mobility patterns has become clear (Athey et al. 2021; Moro et al. 2021; Xu et al. 2019; Wang et al. 2018; Heine et al. 2021; Phillips et al. 2021), the question of how to design more inclusive, connected cities remains an open one. Ever since Jane Jacobs published her seminal works that championed the community-based approach to city building (Jacobs 1961), urbanists and social scientists have worked to develop our understanding of how to build stronger and more equitable communities in cities (exemplified by Talen 2012).

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. Researchers have since used surveys, interviews, and observational studies to support this argument, qualitatively describing the unique abilities of certain types of these "third places" to host diverse social interactions and highlighting 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). However, while "third places" provide a venue for people to come together, socialize, and exchange ideas, they can also serve as sorting spaces (Nilforoshan et al. 2023; Caetano and Maheshri 2019). Since no one is constrained to any one particular "third space," people self-sort by interests and preferences, which could potentially lead to them being more socially segregated than, for example, workplaces (Oldenburg 1997, Nilforoshan et al. 2023).

Therefore, the extent to which people are segregated in these third spaces remains an open question and a difficult one to study, as it requires comprehensive information on how 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. As our technologies become more sophisticated and ubiquitous, new big data sources allow us to investigate these questions in a statistically rigorous way. In this study, we use mobile phone data tracing over one million devices to quantify how access to different types of gathering places contributes to increasing the exposure of people from diverse income groups to each other at the individual level in Stockholm, Sweden.

This work builds on a growing body of literature that uses large, geospatial data to measure experienced segregation or activity space segregation in urban environments (Wang et al. 2018; Xu et al. 2019; Athey et al. 2021; Heine et al. 2021; Moro et al. 2021; Phillips et al. 2021). This work primarily uses one of three types of data—call detail records (Xu et al. 2019), global positioning system data (Athey et al. 2021; Moro et al. 2021), or social media data (Wang et al. 2018; Phillips et al. 2021; Heine et al. 2021)—in order to create traces of individual urban residents' movements over time. Using these traces, researchers (1) use estimated home locations or social media profiles to infer sociodemographic features, (2) identify which individuals in their dataset are in the same place at the same time, and then (3) calculate a measure of diversity of encounters or exposure between different social groups. These studies vary in both their geographic scale and their sociodemographic characteristics of focus. For example, Athey et al. 2021 calculates experienced racial isolation across the entire US; Xu et al. 2019 estimates exposure between different income groups in Singapore. We join this literature, using CDR data to measure experienced income segregation in the city of Stockholm, following the approach outlined in Xu et al. 2019.

The impact of improving access to various urban amenities on one's daily exposure to diversity has not been thoroughly examined using high-resolution mobility data. Previous studies have developed the methodologies to create indices of social mixing on a fine spatial and temporal scale, but little work has analyzed these indices in order to understand how different types of spaces, places, and urban forms foster or hamper experienced integration. Athey et al. 2021 present various city-level covariates associated with their racial isolation measure—for example, they find that US cities with high levels of exposure between black and white residents are in general denser, higher-income, and exhibit higher-income mobility. Davis et al. 2019 measure segregation specifically with restaurant visits, finding that restaurants are less segregated than residential locations of their visitors. Moro et al. 2021 and Fraser et al. 2024 expand this work, comparing experienced segregation levels in various urban amenities across the US. Abbiasov 2020 builds on this exploratory work by using park closure and renovation data in order to identify a causal relationship between park access and experienced racial segregation in New York City. A considerable gap in the literature remains to explore additional categories of amenities in a causal way.

We contribute to this literature in two ways. First, we identify correlations between the presence of a wide range of urban amenities in a given place and the level of social mixing that occurs there. Second, we exploit disruptions to the road network to identify a causal relationship between amenity access and social mixing.

2. Data and Methods

2.1. Measuring experienced diversity with mobile phone data

We use data tracing 1.5 million mobile phone devices to quantify how different types of gathering places contribute to improving the exposure to people from different income groups at the individual level in Stockholm, Sweden. 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.

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). Our main measurement of exposure to income diversity corresponds to the weighted average socioeconomic distance between individuals located in a given 500 m x 500 m grid cell of Stockholm at a given time, which we call the Experienced Diversity Index (ED), based on the work of Xu et al. 2019.

In order to calculate our experienced diversity measure (ED), we first estimate the socioeconomic characteristics of the cell phone users in our dataset. We focus on income—income is highly predictive of other socioeconomic indicators like educational attainment in our study area and mixing between income groups has been shown to be critical to outcomes like economic mobility (Chetty et al. 2022). We obtain income information from Statistics Sweden at the DeSO level—a geographic unit that approximately corresponds to a population of between 700 and 2,700 (Statistics Sweden 2019). We divide the city of Stockholm into a 500 m x 500 m grid and estimate the 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 corresponding to the area of overlap. Then, for each user, income is assigned based on the grid cell where they spend the most amount of time at night (between 8 pm and 7am) over the course of our study period. This method is well-established in the literature (e.g., Xu et al. 2019) and has been shown to provide accurate results.

Using this information, we calculate a measure of the income 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:

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

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 i in location L at time T is calculated, $ED_{i,L,T}$, we can aggregate up to the diversity of individuals gathered in a given location L at time T, $ED_{L,T}$ or the diversity of encounters by individuals with home location k at time T, $ED_{k,H,T}$ as follows:

$$ED_{L,T} = \frac{\sum_{j \in \text{grid cells}} ED_{j,L,T} \cdot p_{j,L,T}}{\sum_{j \in \text{grid cells}} \cdot p_{j,L,T}} \quad (1)$$

$$ED_{k,H,T} = \frac{\sum_{L \in grid\ cells} ED_{k,L,T} \cdot p_{k,L,T}}{\sum_{L \in grid\ cells} p_{k,L,T}} \quad (2)$$

where $p_{k,L,T}$ is the number of people who live in grid cell k, located in grid cell L at time T. We use $ED_{L,T}$ in order to analyze the diversity of individuals gathered around different amenities, and we use $ED_{H,T}$ to analyze the impact of access to different amenity types from one's home location on their experienced diversity.

2.2. 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 between POI counts in the two datasets at the grid cell level across the categories of clothing stores (Spearman R = 0.77), grocery stores (R = 0.66), restaurants (R = 0.73), home and leisure stores (R = 0.72), and services (R = 0.69), 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 (Stockholms Stad 2019, 2022). 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 Fig. 1.

2.3. Relationship between place diversity and amenity types

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.

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:

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

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

Here, $count_k(m)$ 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).

2.4. Causal effect of increasing travel time to amenities

To assess the potential causal effects of urban interventions on social mixing, we employ quasi-experimental data on temporary road closures, which allow us to identify the impacts of improving access to certain categories of amenities using a two-way fixed effect model. 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 use data on road closures to estimate changes in experienced travel times across the city (see Fig. 2). 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 −0.018, calibrated to be equal to the elasticity of travel demand for leisure amenities with respect to travel time (estimated in Miyauchi, Nakajima, and Redding, 2021).

We obtain the full Stockholm street network and all mapped points of interest (POIs) from OpenStreetMap. 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 between each pair of our 500 m × 500 m 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 m for grid cell i at time t as follows:

$$access_{it}(m) = \sum_{j \in \text{grid cells}} count_j(m) \cdot e^{-\phi \cdot T_{ij}^{car}},$$

where $count_j(m)$ 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).

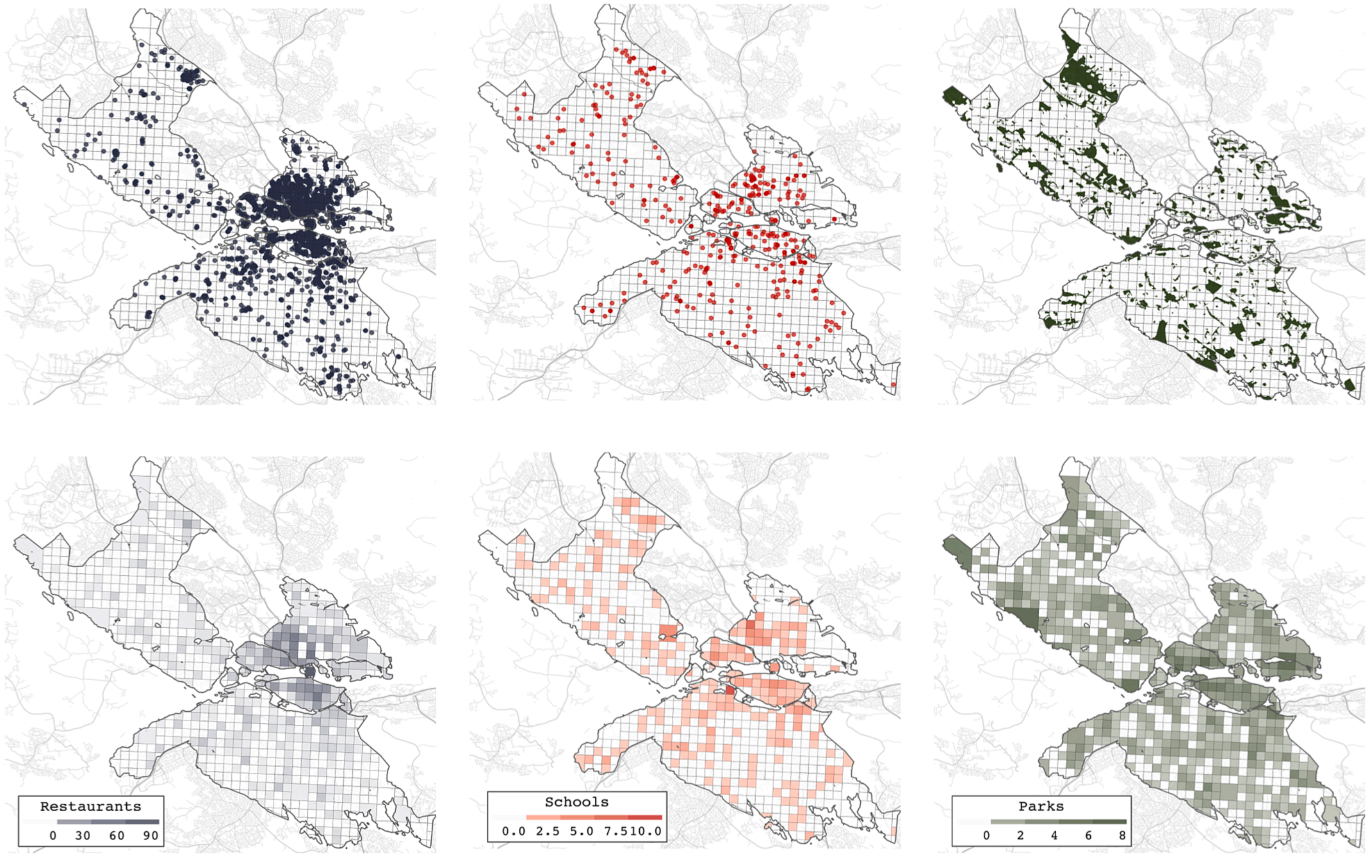

Fig. 1. Amenity locations (top row) and grid-cell-level counts (bottom row) for three example amenity categories: restaurants, schools, and parks. Data for restaurant locations is obtained from OpenStreetMap (OSM), while data for park extents and school locations is obtained from Stockholm Open Data Portal. Park counts represent the total count of parks intersecting a given grid cell.

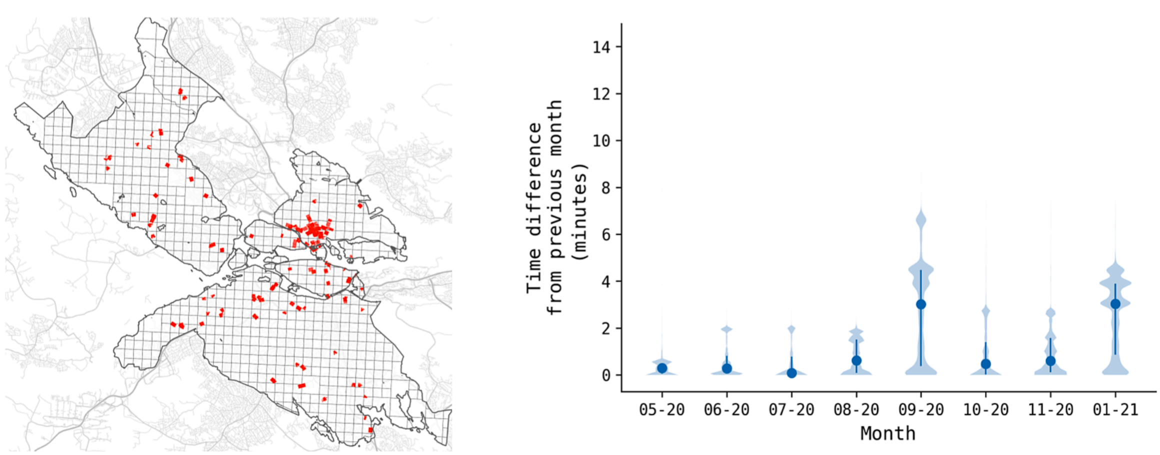

Fig. 2. In Panel A, red dots represent points where roads were closed at some point over the course of our study period. In Panel B, violin plots represent the distribution of absolute deviations in travel times from the previous month—for example, the largest changes in travel times occured between August 2020 and September 2020. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

We first estimate the effect of changes in travel time between two points on volume of travel between them:

$$\log \text{travel volume}_{ijt} = \beta_{mij}\text{travel time}_{ijt} + \mu_{mo} + \mu_{yr} + \mu_{wkd} + \nu_{ij} + \epsilon_{ijt},$$

where travel volume$_{ijt}$ is the volume of trips to grid cell j at time t by cell phone users whose home locations are estimated to be in grid cell i, μ are time fixed effects (monthly, yearly, and weekday/weekend), 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. Again, we use a Beta regression, assuming that experienced diversity $ED_{k,H,T}$ for any grid cell k, y_k, is drawn from a Beta distribution with mean $\mu_{k,t}$ and precision ϕ, where:

$$g(\mu_{k,t}) = \sum_{m \in \text{amenity categories}} access_{it}(m)\beta_m + \alpha_{m(i)} + \theta_{y(i)} + \gamma_{h(i)} \quad (4)$$

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

Here, $access_{it}(m)$ is access to 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. For a given grid cell i, all variation in our access variable is due to road closures.

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 which capture 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 are often located next to one another), 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.

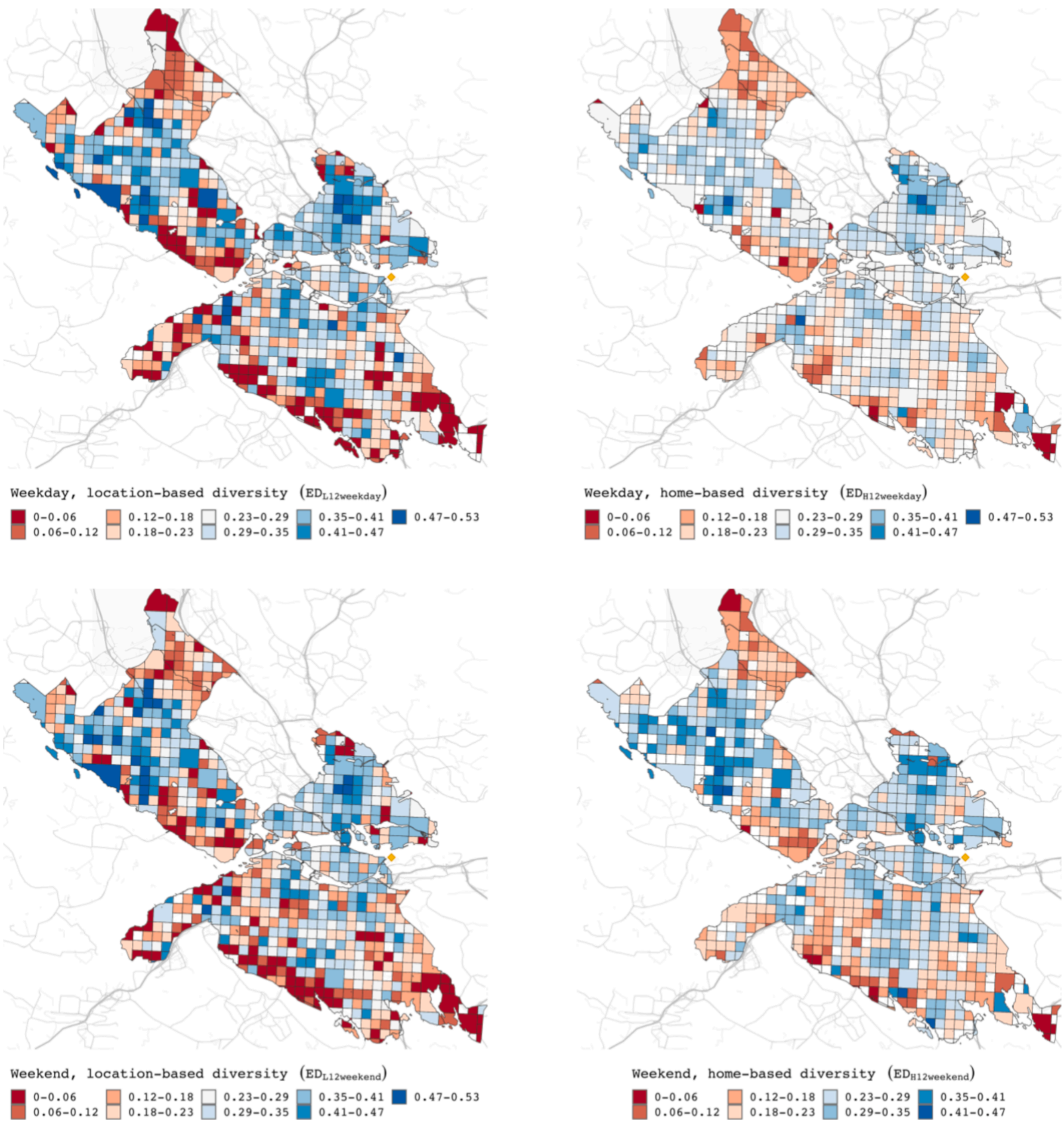

Fig. 3. Experienced diversity by destination and origin home location. Panel A shows the experienced diversity of visitors to each grid cell at noon on a weekday. Red cells (low values) represent more segregated spaces. Panel B shows the average experienced diversity at noon on a weekday by residence location, averaged across all locations that residents of a given home grid cell may be visiting. Panels C and D are analogous to Panels A and B, but show weekend values as opposed to weekday values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Results

Panels A and C of Fig. 3 show daytime experienced diversity across locations in Stockholm for weekdays and weekends, respectively. 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. Conversely, the area in the east of Stockholm surrounding Stockholm University and the urban development of Norra Djurgårdsstaden appears to be a hotspot of high experienced diversity. The wide neighborhood-to-neighborhood variation suggests that access to places with high social diversity is unequal in Stockholm. Panels B and D of Fig. 3 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 Eq. (2)). We see that the two measures are 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 (marked by a yellow diamond on the maps in Fig. 3) exhibits relatively high location-based diversity (Panel A), indicating that the people who gather there are income-diverse; however, the same area exhibits medium to low residence-based diversity (Panel B), indicating that the individuals who live there encounter less diverse groups of people as they move throughout their days.

The spatial distribution of experienced diversity on weekends is quite similar to that on weekdays, as shown in Panels C and D of Fig. 3. However, residence-based experienced diversity is notably more extreme on weekends (Panel D) as compared to weekdays (Panel B), with both darker blue and darker red areas on the map in Panel D.

The clear variation in location-based experienced diversity spurs a natural next question: what exactly is happening in areas with high experienced diversity? We use Beta regression to estimate the relationship between the presence of various types of urban amenities (see Fig. 1) 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 experienced diversity 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 (Tiefelsdorf and Griffith 2007).

Fig. 4 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, parks, and restaurants. These relationships shrink in magnitude but remain significant during weekday hours, 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, indicating that areas with more total bars and total grocery stores are associated with lower experienced diversity, controlling for presence of other amenities and unobserved spatial covariates. Certain of these relationships do not hold during the weekdays: attractions and shops host less-diverse social interactions than other areas specifically during leisure hours.

However, the estimates presented in Fig. 4 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 access to those types of spaces will foster more experienced diversity. First, these estimates do 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 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 more causally-interpretable effects of urban interventions on social mixing, we employ quasi-experimental data on temporary road closures, which allow us to identify the impacts of improving road access

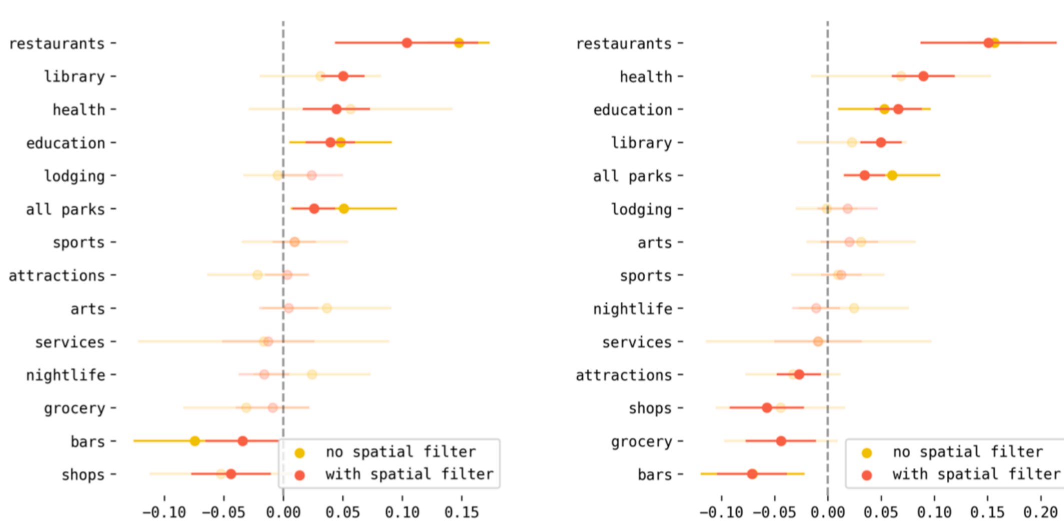

Fig. 4. Regression coefficients representing the relationship between total count of a given amenity type in a grid cell and experienced diversity in that grid cell. The value for amenity type m is analogous to β_m in Equation (3) in the Methods section. Orange datapoints represent coefficient estimates 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"). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

to specific categories of amenities using a two-way fixed effect model. We first verify that higher travel times due to exogenous shocks to the road network do in fact influence travel behavior. We find that there is a significant effect: one minute of increased travel time is associated with a 2.1 % decrease in travel volume, indicating that random changes in access due to road closures do in fact influence travel behavior (Table 1).

Given that fluctuations in travel time have a significant effect on volume of travel, we then measure the impact of changes in access to amenities of different kinds due to these fluctuations on experienced diversity. We quantify the impact of reducing travel times to points of interest across 14 amenity categories on experienced income diversity using a Beta regression model with two-way fixed effects. 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 healthcare establishments, services and parks. Fig. 5 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. Increased access to parks, services and healthcare institutions is associated with higher experienced diversity, whereas more locally-used amenities like grocery stores are associated with lower experienced diversity.

4. 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.

We provide 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 institutions, healthcare establishments, parks, 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, services and healthcare establishments and experienced diversity: temporary, random decreases in access to these spaces due to road closures result in less-diverse encounters for urban residents.

Our results are mixed in that we find that the coefficients on some amenities are significant in our exploratory analysis, but not in our causal analysis. This demonstrates the joint importance of both types of analysis, where each adds nuance to the other. More specifically, the differing results demonstrate that improving access to places that may appear socially mixed does not necessarily lead to more social mixing and that the impact of access on social mixing also depends on the choice alternatives that differ across amenity types. For example, while areas with a high concentration of schools host relatively diverse encounters, changing access to those areas along the road network does not have a significant effect on experienced diversity. This is intuitive—for most, schooling is a mandatory and routine activity, so an increased travel time to school on any given day will not likely affect a student's decision to attend. On the other hand, increased travel time to a park may be more likely influence any given person's decision to visit that park—aligning with our result that both (1) parks host more income-diverse encounters, and (2) increased access to parks is associated with increased diversity of encounters.

Table 1
The results of estimating a regression model describing the relationship between travel time and volume of travel.

	Dependent variable: Log(flow volume)
Travel time	− 0.021***
	(0.003)
Monthly fixed effects	✓
Yearly fixed effects	✓
Weekend fixed effects	✓
OD pair fixed effects	✓
Note:	*p < 0.1; **p < 0.05; ***p < 0.01

Many of our exploratory results align with existing literature (Abbiasov 2020; Fraser et al. 2024; de la Prada and Small, 2024), while our causal findings add nuance to these conclusions. Our findings demonstrate that not all "third spaces" are associated with social mixing; in fact, some are associated with sorting. For example, our finding that increased access to parks enhances social mixing aligns with Abbiasov 2020 and Fraser et al. 2024, and our result that healthcare establishments promote social diversity aligns with Moro et al. 2021. Conversely, we found that grocery stores are associated with higher socioeconomic segregation, consistent with de la Prada and Small 2024.

Some of our findings differ from earlier research. For example, Moro et al. 2021 find that schools in the U.S. are relatively more income-segregated than other amenities, whereas we observed more diverse interactions in areas with a high concentration of schools. This may be at least partially attributable to cultural and contextual differences, as most existing work focuses on the United States and in this study, we focus on Stockholm. In the United States, students are often assigned to public schools near their homes, leading school income segregation to mimic residential income segregation (Rivkin 1994). However, in Sweden, a a more flexible school choice system allows for more mixing across neighborhoods and thus more income-diverse schools (Böhlmark, Holmlund, and Lindahl, 2015). Nilforoshan et al. 2023 report opposite findings to ours in terms of bars and restaurants. They find that in the United States, urban residents appear to self-segregate across restaurants by income — perhaps due to price or cuisine preferences — but not across bars, while our results show the opposite in Stockholm. While cultural differences may explain some of these divergences, another explanation could lie in our limited ability to determine the specific destinations of visits beyond the 500 m resolution of our grid cells. For instance, we cannot fully distinguish visitors to a bar from those visiting a neighboring restaurant, which may impact our results. This issue is further exacerbated due to the high correlation between the number of restaurants and bars in a given area. As a result, the interpretation of our descriptive findings also differs from Nilforoshan et al. 2023. We find that, conditional on the number of restaurants in an area, an increase in the number of bars is associated with lower levels of socioeconomic mixing, while a higher number of restaurants is associated with higher mixing, conditional on the number of bars. This does not necessarily imply that restaurants are more socioeconomically mixed than bars, but rather highlights differences between neighborhoods with more abundant dining options compared to those with more drinking establishments. For example, in Stockholm, restaurants may be relatively more centrally concentrated or situated in areas that attract more tourists than bars. Future work may be able to distinguish more precisely between these scenarios.

This study demonstrates one potential pathway towards isolating the effect of access different urban amenities on social segregation. There is room for our approach to be built upon and strengthened by using different or more detailed data. Using road closures as an instrument for fluctuating accessibility as we have done in large part limits our study population to car drivers and bus riders, as pedestrians and train passengers are not likely to be affected by road closures in the same way. Future work could explore pedestrians and transit riders specifically by focusing on, for instance, weather events which make walking difficult or disruptions to public transit service, respectively; alternatively, future work could look specifically at the impact of closures of specific amenities instead of looking at accessibility via the transportation network, as demonstrated in Abbiasov 2020. Another approach could use more detailed mobility data to calculate experienced travel times by different modes instead of estimating them from OpenRouteService. This

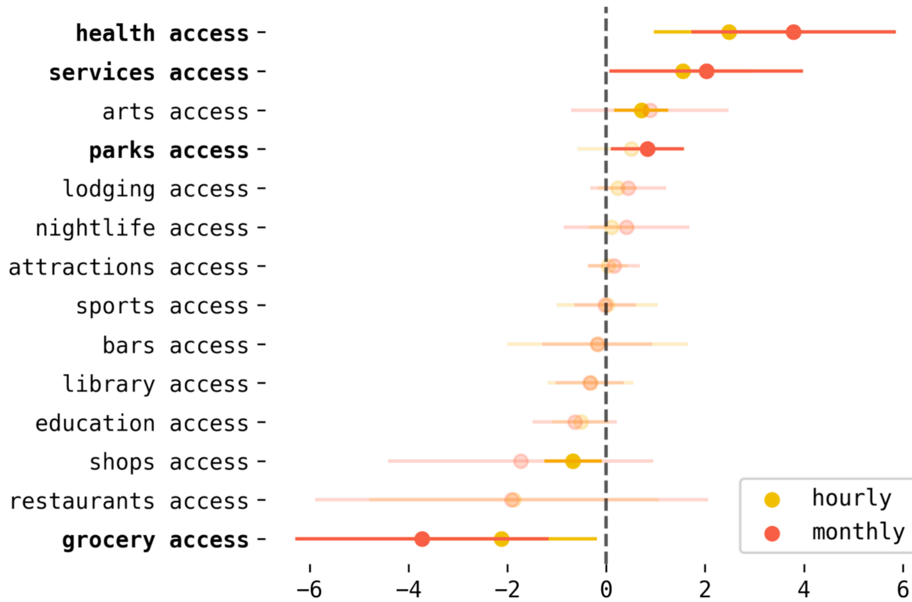

Fig. 5. Regression coefficients representing the relationship between access to a given amenity type from a grid cell and experienced diversity by people living in that grid cell. Coefficients are analogous to β_m in Equation (4). Yellow points represent results at the hourly level, while pink points represent results when data is aggregated to the monthly level. Error bars represent a 90% confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

approach would allow for the separate estimation of accessibility changes with road closures by different modes of transportation; however, it would require far more detailed data than that which we have access to in order to predict mode choice and accurately calculate travel time, such as extensive travel surveys or extremely detailed GPS data. These more precise instruments would allow for a stronger argument for causality, overall helping with strength and interpretation of the results.

One major limitation of this work is that our experienced diversity index measures the level of co-presence of individuals from diverse income groups, which provides the conditions for establishing meaningful social interactions across different groups, but does not guarantee such interactions occur. Nevertheless, co-presence between diverse groups of people may in and of itself reduce prejudice and social tension (Anderson 2011) and has been the focus of previous studies in Stockholm and elsewhere as an important dimension of segregation (Nilforoshan et al. 2023; Rokem and Vaughan 2019). Moreover, diversity of co-presence has been shown to be a strong indicator of the diversity of social relationships (Xu et al. 2019; Chetty et al. 2022). Some previous research has shown that face-to-face exposure—as captured by proximity—and social interaction are indeed complementary. For example, Büchel and Ehrlich 2020 exploit an exogenous change in travel times to show that distance is highly detrimental to interpersonal exchange. However, when interpreting our results it is important to keep in mind that the index we have created cannot capture actual interactions between people, and that simply being in the same space does not necessarily mean that two individuals are interacting. Future work that can isolate meaningful interactions or the formation of social relationships from simple co-presence would add nuance to the results presented here.

It is important to note that our approach assumes that all residents of the same 500 m x 500 m grid cell share the same income level, an ecological fallacy as outlined in Openshaw 1984. If detailed data on within-unit income distribution or individual income level linked with mobile phone data is available, it would be meaningful for future work to quantify exactly how much bias this induces into measures of experienced segregation. Further, our approach relies on cell phone data, which represents a biased subset of the total population of Stockholm. While Sweden has very high rates of mobile phone ownership (125 cell phone subscriptions per person according to The World Bank, (2023), our data may be income- and age-biased, as low-income residents, children, and elderly residents may be less likely to own and regularly use a mobile phone.

There are many open questions in this space for future research. We study the relationship between urban amenities and social mixing specifically in the context of Stockholm, Sweden. Applying the same methodology in other parts of the world in order to understand the generalizability of these results across cultural contexts and urban layouts would be a valuable next step. Further, while we have identified a relationship between experienced integration and a few specific types of spaces, others remain unexplored; for example, how do mobility constraints imposed by road and transit networks impact experienced integration? How do land-use configuration and street morphology play into experienced integration? 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.

CRediT authorship contribution statement

Cate Heine: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Timur Abbiasov:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Paolo Santi:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Carlo Ratti:** Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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