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Understanding neighborhood income segregation around the clock using mobile phone ambient population data

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This study examines the temporal changes in income segregation within the ambient population around the clock using mobile phone big data. It employs ordinal entropy, a metric suited for measuring segregation among ordered groups, to quantify the level of segregation among eight income groups within micro-geographic units throughout the 24-h period on a weekday and a weekend day in the urban core of Guangzhou, China. The study further decomposes daily segregation by location and time profile. We identify urban functions and neighborhood contexts relevant for income segregation and explore their temporal variation. Using group-based trajectory analysis, we classify daily segregation trends among 400 m urban grids into seven distinct trajectories for both weekday and weekend. Our findings confirm that segregation fluctuates constantly. The role of local urban functions, particularly retail, accommodation, and offices, and neighborhood context, such as the number of residents and the share of non-local migrants, exhibits a significant temporal rhythm. The seemingly convoluted 24-h segregation time series among urban grids follow just a few distinct trajectories with clear geographical patterns. There is limited variability at individual grids both over the course of a day and across days. Shifts across different trajectory types between weekday and weekend are rare. The dynamic daily segregation in the ambient population per se may be an enduring characteristic of neighborhoods and a real-time channel for neighborhood contextual influences, potentially fueling long-term residential segregation and neighborhood change.

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Introduction

Modern urban life has long been characterized by social and spatial separation between populations of different race/ethnicity and socioeconomic status. A large body of social science literature has noted the profound influence of inter-group segregation/integration on individual well-being, urban development, and society at large (Chetty et al. 2016; Wilson 2012). Most studies on segregation have so far focused on the residential context. While the residential space constitutes a major anchor point of everyday life and is predictive of where people spend time, it does not capture the entirety of the exposure contexts people frequent during daily activities in urban (Cagney et al. 2020; Matthews 2011) and rural settings (Kwiatek et al. 2024). Individuals from segregated neighborhoods may be exposed to diverse contexts when conducting routine activities and individuals from diverse neighborhoods may only sort into spaces with people alike. In other words, people experience segregation/integration both inside and outside the residential space.

With the introduction of activity space and time geography concepts and methods, segregation research begins to move beyond the static residential context to activity spaces by using individual location tracking or ambient population counts. The extent to which the context specified by researchers aligns with the true geographic and social context of influence is a function of both space and time (Kwan 2012). Along the spatial line, empirical studies find that compared to the residential space, there is less racial segregation in the workplace (Ellis et al. 2004; Hall et al. 2019) and greater racial and social heterogeneity in activity spaces (Jones and Pebley 2014; Zhang et al. 2022a). The temporal uncertainty has so far received limited attention. Recent research on temporal changes of social segregation reveals significant fluctuations of social composition on both the global and local scales throughout the day (Le Roux et al. 2017; Park and Kwan, 2018; Zhang et al. 2022b).

The present study moves beyond the temporally static understanding of segregation and delineates segregation profiles of micro-geographic units over the course of a day. We further decompose income segregation across time and space to reveal how different activities elevate or reduce segregation and the sequencing of segregation levels. Along the spatial dimension, we explore how functions of neighborhoods, such as residential, public, institutional, and commercial spaces, factor into the ebbs and flows of segregation throughout the day. Along the temporal dimension, we delineate the time profile of income segregation by finding common segregation trajectories across neighborhoods using group-based trajectory analysis (Nagin 2005). In addition, we test the extent to which these time profiles are stable at individual grids across weekday and weekend. To do so, we draw on hourly ambient population data of 8 income groups at 400 m grid cells in the urban center of Guangzhou from China Unicom Inc., a major Chinese telecommunication company.

Our results will provide insights into long-standing questions in the human mobility and urban sociology literature. For example, to what extent and why do groups of different backgrounds cross social boundaries? Are differences in amenities (e.g., groceries) and institutional resources (e.g., education, medical care) key drivers of urban mobility (Small and McDermott 2006)? While many have argued that changes in neighborhood social processes are slow and neighborhood contexts such as residential segregation are enduring (Hwang and McDaniel 2022; Sampson 2012), does this endurance claim hold true for segregation beyond the residential space?

Background

Residential income segregation. Income inequality, a phenomenon where income is not uniformly distributed in the population, is a key prerequisite for income segregation, defined as the uneven geographic distribution of income groups. Income inequality alone, however, is not sufficient to create income segregation. With the presence of income-correlated residential preferences, housing market, and housing policies, income inequality may translate into income segregation in residence (Reardon and Bischoff 2011).

Research on income segregation centers around three lines of inquiry. The first line focuses on the development, estimation, and validation of segregation indices (Leung-Gagné and Reardon 2023; Massey and Denton 1988; Reardon et al. 2006). A second body of research describes the level of income-based segregation across cities and its trend. Studies generally find that even after adjusting for sampling bias, income segregation has been on the rise in recent decades in the US, especially among families with children (Reardon et al. 2018). A cross-national study between France and the US reports that socioeconomic segregation in large metro areas is higher in the US than in France and that the high-income are the most segregated income group in both countries (Quillian and Lagrange 2016). In racially homogeneous China, social segregation research has received considerable academic attention. Since the economic reform at the turn of the twenty-first century, China has gone through drastic social changes, with segregation going from minimal under the planned socialist economy to a level comparable to the West (Shen and Xiao 2020).

Another strand of research examines the consequences of income segregation, arguing that residential segregation creates gaps in the quality of public goods, institutional resources, opportunities, social processes, norms, and the environment between neighborhoods (Reardon and Bischoff 2011; Sampson et al. 1997; Wilson 2012). As such, high-income neighborhoods are able to self-reinforce their advantages while low-income segregated neighborhoods are further alienated from the "mainstream" society and suffer from resource deficiencies. When linked to individual outcomes, empirical studies document that income segregation widens the gap of educational attainment and elevates the risk of infant mortality (Mayer 2002; Mayer and Sarin 2005). Since children and the elderly are more spatially constrained, segregation in the residential space may be more consequential for these groups (Reardon et al. 2008).

Segregation beyond the residential space

So far, existing literature on social and income segregation is predominantly about the residential context. As people conduct daily activities, however, they typically cross the borders of their residential neighborhood and get exposed to contexts they visit (Cagney et al. 2020). The experience of segregation, be it race-based or income-based, therefore, is not limited to the residential space. A body of research compares segregation in the residential context against segregation in the workplace (Ellis et al. 2004; Hall et al. 2019), leisure activity locations (Toomet et al. 2015). More recently, studies move toward a holistic definition of activity spaces and the segregation experience therein. Research has evolved along two lines: one focuses on locations (e.g., cities or metro areas) and the other on individuals. For instance, based on large-scale big location data derived from social media and mobile phone usage, studies show that activity-space-based racial segregation differs from that in the residential context across cities (Athey et al. 2021; Candipan et al. 2021). At the individual level, Wang et al. (2018) show that the sociodemographic characteristics of non-home neighborhoods people visit resemble those of their residential neighborhood and the immediate surroundings with big social media data. However, there exists substantial heterogeneity in the characteristics of exposure contexts by race after adjusting for the residential surroundings (Cai et al. 2024). Ethnographic studies have long observed that residents of the same neighborhood may sort into spaces unlike their home during routine activities in very different ways. Some Blacks may entirely withdraw social contact with Whites after work, while others become White-behaving and interact with Whites far more frequently (Anderson 2022). In a study on social segregation, Zhang et al. (2019) demonstrate with GPS tracking data that individuals who reside close by, indicative of similar socioeconomic backgrounds, exhibit divergent mobility patterns and varied level of exposure to segregation in routine activities. These observations call attention to the more complex experience of segregation beyond the static residential neighborhood. Methodologically, studies neglecting the out-of-home context run the risk of mis-specifying the true causally relevant context, which in turn may lead to inference errors (Kwan 2012).

Like the study of residential segregation, studies investigating racial segregation in activity spaces are by far the most common. Research on income segregation in activity spaces is scarce. Using massive individual mobile phone location traces, Moro et al. (2021) reveal that mobility patterns, shaped by individuals' tendency to explore new and socially different places, play an important role in individuals' experience of income segregation. A Guangzhou-based study suggests that there is drastic segregation between the high- and low-income groups in out-of-home activities (Zhou et al. 2015).

Temporal variations of segregation. Whereas studies are increasingly aware of the spatial extension of segregation by incorporating activity space contexts through the use of individual location tracking data (e.g., geotagged twitters, GPS tracking, travel diaries) or ambient population data (Cai et al. 2022), there remains limited consideration of the temporal variation of segregation. With few exceptions, an understanding of the dynamics of segregation over the course of a day remain elusive. Existing studies suggest that the degree of segregation varies hour by hour as a result of human mobility. Using activity-travel diaries in Atlanta, Park and Kwan (2018) find that people's experienced racial segregation varies throughout the day, with higher segregation levels at night than during the day. In Paris, researchers similarly reveal with a large-scale travel survey that education-based segregation is lower during the day than at night (Le Roux et al. 2017) and that the social compositions are reshuffled due to daily human mobility. Zhang et al. (2022b) show that at the city level, segregation by education is stronger at night and on weekday in central Beijing. They further observe higher variability in segregation over time on weekday than weekend, particularly for locations with concentrated employees and residents. Using mobile phone data, Silm and Ahas (2014) find similar results in Tallin: ethnic segregation is higher at night, on weekend, and in winter. Yet, studies on temporal variations of segregation remain largely descriptive.

Urban functions, neighborhood context, and the enduring segregation. While a few pioneer studies have manifested clear temporal variations in segregation around the clock, the reasons behind such variation remain under-explored. In the literature of residential segregation, inequalities in resources, network, and opportunities across the urban space shape residential sorting processes and segregation in major ways through school choices and gentrification, among others (Hwang and McDaniel 2022). Segregation, in turn, structures existing inequalities in complex ways in the long run. In the short term, however, it largely remains unclear whether such disparities in institutions, amenities, and resources also function as a segregation facilitator or inhibitor on the day-to-day basis and in contexts beyond one's home. The urban sociological and geography literature has long noted that urban functions (e.g., amenities and institutions) and neighborhood social context (e.g., social cohesion, networks) fundamentally shape daily human mobility and local social composition. In his ethnographic work, Anderson (2011) observes how visitors to Rittenhouse Square, an urban park in Philadelphia, change drastically throughout the day: diverse groups of all ethnic and class backgrounds in the morning, nannies and middle-class mothers during midday, and wary passers-by in the evening. In other words, the social profile of frequent users of a scene defines the location and as population composition reshuffles with time, the character of the location also evolves. Jacobs (1961) also elaborate in her observation how street activity shifts after business hours. Due to uneven spatial distribution of resources, people may hunker down in their own neighborhood for everyday needs or are compelled to neighborhoods beyond home for resources that are not available otherwise (Browning et al. 2022; Small and McDermott 2006), thus fluctuating the level of segregation in both origin and destination locations. Research on workplace segregation shows that the presence of firms and institutions draw employees of different social backgrounds to the same location, thereby reducing the level of segregation nearby (Ellis et al. 2004; Hall et al. 2019). Such ups and downs near employment sites likely hold true on a routine basis. Similarly, Athey et al. (2021) show with large-scale GPS data that people experience less segregation in their leisure activity locations (e.g., entertainment, retail, and eating establishment) and more segregation in institutional locations than their home environment. It remains unclear, however, whether the segregation-alleviating/exacerbating effects of urban functions also change with time (temporal heterogeneity). Do these effects only operate during opening hours or constitute a defining feature of the local context and are thus at work around the clock?

To sum up, existing segregation research has the following key caveats. First, while extensive attention has been paid to segregation in the static residential context, much less is known about segregation in activity space and how it fluctuates over the course of a day. With the increasing daily human mobility, the local social composition likely varies on a constant basis. Second, even with studies noting temporal variations in segregation, the mechanism behind varied temporal trajectories of segregation remains under-explored. How does local segregation covaries with the presence of urban functions and neighborhood context? Third, rooted in the classic segregation research, most existing studies so far center around the segregation at the aggregate level including cities and metro areas. Segregation at the micro units, the immediate environment that individuals are directly exposed to, is less researched. Last, with ethnic/racial segregation in the West drawing most academic attention, less is known about income segregation in non-Western contexts. The present study uses central Guangzhou as a case to address these caveats in the literature.

Data and method

Data

Study area. This study focuses on the central urban area within the city ring expressway (Huancheng Expressway) of Guangzhou, a major metropolis in Southern China. Specifically, we only focus on the central urban areas of Yuexiu, Haizhu, Tianhe, Liwan, and Baiyun Districts. The study area includes a total area of 213.93 square km with an average population density of 16.01 thousand people per square km. Figure 1 illustrates the study area relative to the city of Guangzhou.

Fig. 1 Study area. The study area is the central part within the city ring expressway (Huancheng Expressway) of Guangzhou.

Mobile phone big data. This study analyzes income segregation using ambient population data of central Guangzhou provided by China Unicom Inc., which takes up 24% of the telecommunication market share in the city of Guangzhou. The location information of phone users is recorded when a phone call, text, or data-use request is made. China Unicom further classifies individual users into one of the eight income levels using machine learning techniques based on the housing price of the residential community identified from the geolocations, the price of phone model, the number of leisure locations visited, the number of long-distance trips (inter-city and abroad), travel mode (flight/rail/automobile), and phone bills. Based on their classification, the poor (level 1) and low-income (level 2) correspond to an annual individual income of less than 50,000 yuan. The lower middle-income group (level 3) represent people with an annual income ranging between 50,000 and 100,000 yuan. The middle-class (level 4) earns between 100,000 and 180,000 yuan. The upper middle-class (level 5) includes individuals with an annual income of 180,000 to 300,000 yuan. The high-income class (level 6) comprises those with an annual income of 300,000–500,000 yuan. The rich (level 7) and super-rich class (level 8) earn over 500,000 yuan each year.

China Unicom Inc. estimates the total population size on an hourly basis for each of the eight income groups at 400 m grid cells.[1] Based on the share of telecommunication companies, it then extrapolates the size of ambient population to match the total population of Guangzhou (Zou et al. 2020). There are a total of 1263 grid cells in the central city.

In the present study, we use mobile phone data of a weekday (Wednesday, June 10th, 2020) and a weekend day (Saturday, June 13th, 2020). Recent empirical research shows that the population estimate of the China Unicom dataset is consistent with that from the population census (Song et al. 2023).

Urban functions and neighborhood context. To understand how urban functions shape local income segregation, we consider grid-level urban functions based on point of interest data (POI) from a major map navigation company. The data include information such as name, type, and geographic coordinates of each POI. Following existing literature, we consider seven broad categories of POIs: transportation, institutions (schools, hospitals, and public facilities), residential, retail (supermarkets, wholesale markets, street markets, and shopping centers), accommodation, entertainment, and office (Athey et al. 2021). Transportation facilities comprise railway stations, long-distance bus stations, subway stations, and civil airports. We have two categories for schools: primary and secondary schools and post-secondary education institutions that offer academic, advanced vocational, athletic, and art training programs. Hospitals include general and special hospitals and community hospitals. Public facilities encompass convention centers, museums, libraries, parks, touristic attractions, and religious places. Entertainment facilities consist of karaoke bars, bars, internet cafes, clubs, and other common recreational and nightlife facilities. We use a binary variable to indicate proximity to each of the above urban functions, with 1 representing that there is at least one POI in the unit and 0 otherwise. In addition, we include two neighborhood sociodemographic characteristics from population census at the neighborhood level: the number of residents and share of nonlocal population.

Due to missingness in POI data, we drop 70 grids in the regression analysis. The resultant analytical sample in the regression analysis is 1193.

Segregation measures. The literature has established a series of metrics to quantify different aspects of segregation (Massey and Denton 1988), with most metrics developed in the context of residential segregation and at a global scale such as cities or metro areas. There is a growing interest in capturing segregation at the micro scale (Wong and Shaw 2011; Zhang et al. 2022a, b). A few studies also develop activity-space-based segregation measures (Wong and Shaw 2011). Another strand of research begins to focus on individual experience of segregation instead of geographic units (Wang et al. 2018).

Measures of income segregation. The majority of segregation indices are developed and applied in the context of racial segregation. The dissimilarity index or the D index is perhaps the single most used segregation measure in the literature. It represents the proportion of a given group that would have to relocate to achieve an even population distribution (Duncan and Duncan 1955). However, for multi-group scenarios, which is often the case for segregation by income, a series of pairwise D indices need to be computed between combinations of groups (Massey and Denton 1988). The information theory index (entropy) and Simpson's interaction index (or the Herfindahl index) are more frequently used in multi-group cases. Others, however, have noted that these measures require pre-defined discrete and typically unordered categories[2] and are therefore unsuitable for continuous variables (Yao et al. 2019). The neighborhood sorting index, ordinal entropy index, and rank-order entropy index[3] have been proposed (Reardon and Bischoff 2011) for income segregation. Most of the metrics discussed above focus on the overall segregation level of cities or metro areas summarized from individual area units with a single value representing the level of segregation/integration of the entire city or region. Local measures, by contrast, consider the internal heterogeneity of segregation within a city or metro area (Wong 2008).

Measures applied in the around-the-clock setting. A few studies have applied aforementioned metrics to investigate temporal changes of segregation. For instance, using travel survey data, Le Roux et al. (2017) employ a series of segregation index including the entropy and D indices to understand the social composition dynamics throughout the day in the Paris region. Using location-based service big data, Zhang et al. (2022b) examine temporal variations of D-index-based educational segregation among the ambient population at both global and local levels in central Beijing.

In this study, we adapt a multi-group index to measure income segregation at the micro-geographic level: the local ordinal entropy index:

$$E_i^O = -\frac{1}{J-1}\sum_{j=1}^{J-1}(c_{ij}\ln(c_{ij}) + (1-c_{ij})\ln(1-c_{ij}))$$

where c_{ij} is the cumulative group share that represents the sum of the proportion of the population in groups less than or equal to each category j in unit i. J is the total number of distinct income groups. First proposed by Reardon et al. (2006), ordinal entropy reflects the ordered nature of the income groups but does not require an estimation of the income distribution. Because entropy is a measure for diversity, we take the reverse of the metric and rescale it to 0 and 100, with a higher value representing a greater degree of income segregation. In sensitivity analysis, we run all the analyses using simple information theory entropy:

$$E_i = -\sum_{j=1}^{J}\pi_{ij}\ln(\pi_{ij})$$

where π_{ij} is the proportion of income group j in unit i.

Methods

We first calculate the local segregation indices for each hour of the two observation days and describe the temporal and spatial patterns. For each individual grid cell, we then get two time series, each of length 24, where each data point represents the level of local segregation for a specific hour. To decompose income segregation by urban functions, we perform multilevel models predicting income segregation of each hour with grids (level 1) clustered in neighborhoods (level 2) (Raudenbush and Bryk 2002). The rationale for adopting a multilevel approach is twofold. First, grid cells are arbitrarily defined units, which do not align with the natural boundary of many social processes related to local policies, resources, and social organizations. Clustering grids by neighborhoods allows us to capture factors that operates at a higher geographic level. Indeed, intra-class correlations based on null models are non-trivial throughout all temporal models (weekday models: mean = 0.177, sd = 0.016; weekend models: mean = 0.153, sd = 0.017), justifying our choice of multilevel modeling. Second, residential population and the share of nonlocal residents are measured at the neighborhood level. Disaggregating them to arbitrarily defined grid cells would introduce additional noise to the measures. The multilevel model takes the following form:

$$Y_{ikt} = \alpha_{kt} + \sum_{p=1}^{P}\beta_{pt}X_{pikt}\,(\text{Level1})$$

$$\alpha_{kt} = \gamma_{t0} + \sum_{q=1}^{Q}\gamma_{qt1}Z_{qk} + \delta_{kt}\,(\text{Level2})$$

where Y_{ikt} is the ordinal entropy value of unit i located in neighborhood k at time t, α_{kt} is an intercept term that varies by neighborhood membership k and time t, X_{pikt} is unit-level predictor p for unit i in neighborhood k at time t (with associated coefficients β_{pt}), Z_{qk} is a neighborhood-level predictor q for neighborhood k (with associated coefficients γ_{qt1}), and δ_{kt} represents random effects for the intercept. We then collect and visualize the model coefficients β_p's across the 24 hourly models by each urban function for the two observation days. Coefficients from the models are indicative of the correlation rather than causality between urban functions and income segregation. We conduct additional analysis predicting the standard deviation of income segregation to show how urban functions and neighborhood context relate to variability of segregation within each day.

Table 1 Descriptive statistics.

	Mean	SD	Min	Max	N
Income segregation					
Ordinal entropy (rescaled) weekday	60.300	8.140	14.949	96.280	1263
Weekend	60.286	8.090	0	100	1263
SD of ordinal entropy					
Weekday	3.036	1.960	0.378	15.419	1263
Weekend	2.738	1.893	0.366	18.425	1263
Urban functions					
Transportation	0.095	-	0	1	1193
Education					
Primary/Middle school	0.516	-	0	1	1193
Post-secondary education	0.213	-	0	1	1193
Hospital					
General/Specialty	0.205	-	0	1	1193
Community	0.197	-	0	1	1193
Residential	0.733	-	0	1	1193
Retail					
Supermarket	0.393	-	0	1	1193
Wholesale market	0.157	-	0	1	1193
Street market	0.065	-	0	1	1193
Shopping center	0.321	-	0	1	1193
Public facility	0.487	-	0	1	1193
Entertainment	0.478	-	0	1	1193
Accommodation	0.490	-	0	1	1193
Office	0.504	-	0	1	1193
Neighborhood characteristics					
#Residents (hushu, 1000)	2.331	1.645	0.111	14.813	1193
Share of non-locals (%)	30.849	22.273	0	97.442	1193

To delineate the time profile of segregation trajectories, we apply group-based trajectory analysis to identify distinct trajectory groups with the assumption that there exist multiple latent subgroups in the segregation time series (Nagin 2005). As a special case of latent class growth curves model, group-based trajectory modeling is suited for finding trends in time series data. The model takes the following form:

$$Y_{it} = \beta_0 + \beta_{1m}(T_t) + \beta_{2m}(T_t^2) + \beta_{3m}(T_t^3) + e$$

where Y_{it} is the ordinal entropy of unit i at time t. It regresses on a polynomial function of time T. Within each identified trend or group m, the units share the same trajectory defined by a polynomial regression on time (linear, quadratic, or cubic). The method has widely been applied in fields such as individual health outcome trajectories (Nagin and Odgers 2010) and crime trends at micro-geographic units (Weisburd et al. 2012; Wheeler et al. 2016). To find the best fitting trajectory model, we vary the number of latent groups and the degree of polynomial terms of time T: T^1 (linear), T^2 (quadratic), and T^3 (cubic). Since our ambient population measures are continuously tracked, our data are free from problems of missing data and sample attrition commonly seen in similar analyses. We select the best fitting model based on BIC while keeping each trajectory meaningfully different from others. We perform analysis using the `gbmt` package in R. Last, we plot the spatial distribution of identified trajectories in the city and inspect the transitions in group membership across the two sampled days.

Results

Descriptive statistics. Table 1 shows the descriptive statistics of ordinal entropy of income-based segregation, urban functions, neighborhood characteristics. The overall distribution of segregation does not vary substantially by day. The ordinal entropy has a mean value of 60.300 (sd = 8.140) on weekday and 60.286 (sd = 8.090) on weekend. Figure A1 in Appendix are four snapshots of income segregation on weekday (panel A) and weekend (panel B). As expected, the further apart two time points, the less correlated they are, with daytime least correlated with nighttime segregation. This holds true for both weekday and weekend. Between weekday and weekend hours, the correlation is moderately lower than correlation within the same day. For the same hour, the segregation on weekday and weekend shows a moderately high correlation, with Pearson's correlation coefficients ranging between 0.728 and 0.869. The correlation is lowest during the daytime hours (9 a.m.–6 p.m.) and highest during the late night and early morning period (7 p.m.–8 a.m.). Full details of pairwise correlation are shown in Fig. A2 in Appendix. Within individual grids, the segregation level fluctuates hour by hour and the degree of fluctuation varies by unit, with total within-unit variability reaching as high as 18.425% and as low as 0.366% throughout the day. Both extreme values are in weekend segregation time series, signifying a more polarized distribution of income groups in certain areas on weekend. Figure 2 visualizes the geographical distribution of standard deviation of income segregation throughout each day. As people commute for work and engage in diverse social activities on weekday, there is higher overall variability on weekday (mean = 3.036, sd = 1.960) than weekend (mean = 2.738, sd = 1.893).

Spatially, the distribution of income segregation shows a non-trivial level of clustering and the degree of concentration varies by time of day based on Moran's I statistic ($p < 0.001$ for all hours across 2 days). Throughout the 24-h period, spatial clustering of income segregation is higher during the night than day for both weekday and weekend.

Decomposing income segregation

By location. Figure 3 summarizes the multilevel regression coefficients with 95% confidence interval of proximity to six urban functions and neighborhood socio-demographic characteristics predicting hourly income segregation for weekday and weekend. The coefficients are from models with all other functions and characteristics controlled. The results suggest that income segregation is related differently to these feature types. On average, the level of income segregation is most strongly predicted by the presence of retail, accommodation, and office functions as well as neighborhood contextual characteristics such as residential population and the share of non-local migrants. Note, however, that all our results are correlational.

Furthermore, the time series of our regression coefficients strongly indicate the temporality of these locational effects. In other words, the role of places is not frozen even over short periods of time such as an hour and is instead highly dynamic. Of all the locations, the presence of retail, accommodation, and office have the most consistent and strong impact on income segregation around the clock. In particular, proximity to all types of retails is associated with higher levels of segregation. Throughout the 24-h period on both days, the presence of supermarket in the grid is related to higher income segregation. With some fluctuations, this impact is slightly stronger on weekend than weekday. Except for late afternoon, the presence of wholesale market shows a similarly consistent positive correlation with segregation. Street markets, which typically appear on weekend, is positively related to segregation during the daytime on weekend (9 a.m.–4 p.m. and 7 p.m.–9 p.m.). Large shopping centers also increase local income segregation during the day on both weekday (7 a.m.–4 p.m.) and weekend (7 a.m.–2 p.m., except for 9 a.m. and 1 p.m.). By contrast, proximity to accommodations is related with lower income segregation and this relationship is

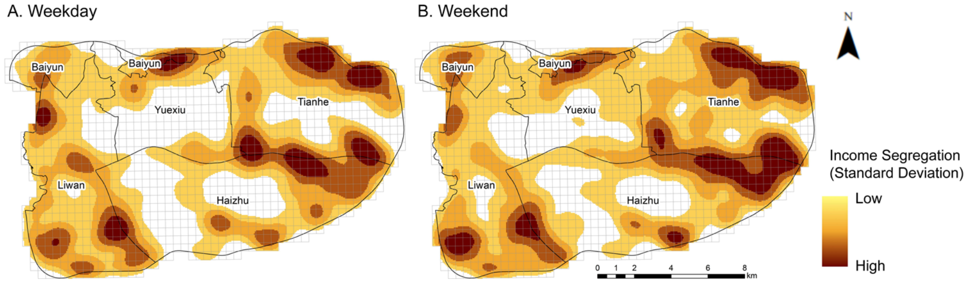

Fig. 2 Spatial distribution of standard deviation of income segregation on weekday and weekend. The distribution of income segregation shows spatial clustering and the degree of concentration varies by weekdays (**A**) and weekends (**B**).

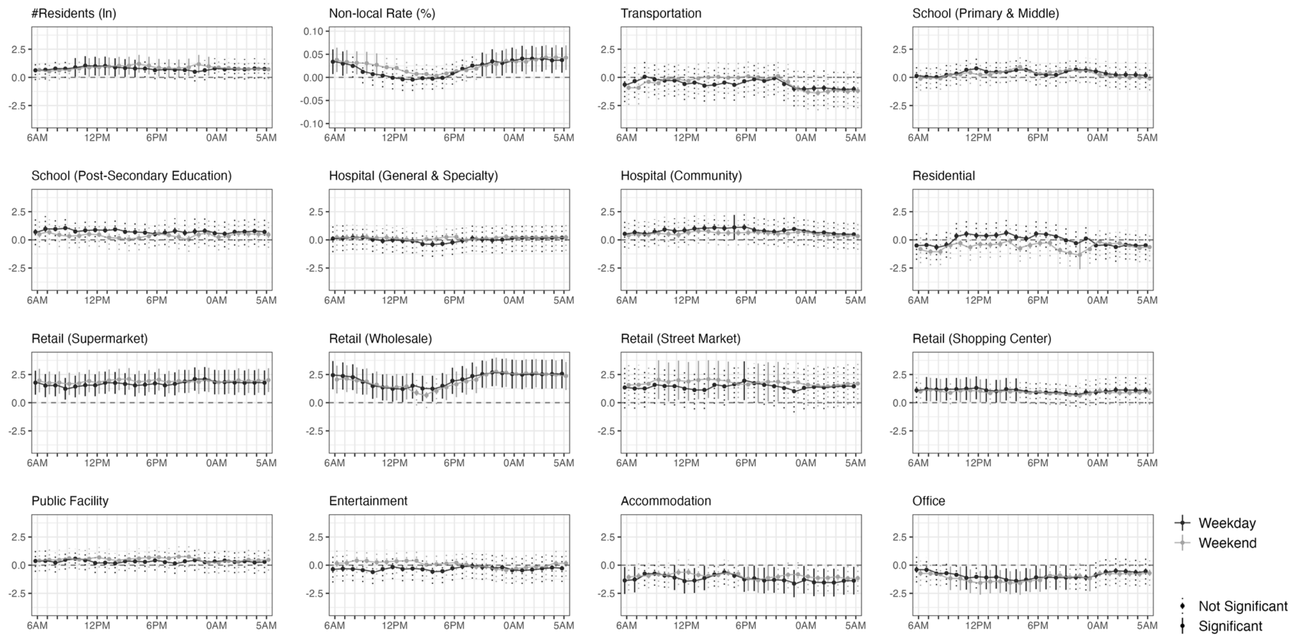

Fig. 3 Coefficients from hourly segregation models. The hourly income segregation for weekdays and weekends is related differently to features of urban functions and neighborhood socio-demographic characteristics.

more pronounced and persistent on weekday (all day, except for 8 a.m.–10 a.m. and 3 p.m.–5 p.m.) than weekend (6 p.m.–8 p.m.). Similarly, having office buildings is linked with less observed segregation on average on both days (weekday: 11 a.m.–9 p.m., except for 12 p.m.; weekend: 9 a.m.–6 p.m. and 0 a.m.). While there is some difference in the trend of weekday and weekend coefficients, the role of urban functions is generally unchanged across days except for street market and accommodation.

Both neighborhood socio-demographic characteristics significantly predict local income segregation. Specifically, the number of residents shows a positive relationship during 10 a.m. and 4 p.m. on weekday and 11 a.m. to 0 a.m. on weekend. This largely picks up the role of residential spaces in the model, which becomes statistically insignificant after the inclusion of the residential population size. Interestingly, the share of non-local population has a positive correlation on segregation between 9 p.m. and 7 a.m. on weekday. This impact is more extended on weekend (9 a.m. to 10 a.m.). Both patterns can be explained by non-locals' spatiotemporal pattern of employment.

We perform additional analysis regressing daily standard deviation of income segregation on urban functions and neighborhood context (see Table A2 in Appendix). Results show that the presence of major transportation facilities is positively correlated with daily variability in income segregation, particularly on weekend. On the contrary, primary/middle schools, residential space, supermarkets, and accommodations all negatively predict variability net of other factors.

It should be noted, however, that the observed relationship between urban functions and hourly segregation is correlational. In theory, urban functions and segregation may have a more complex and reciprocal relationship, which is beyond the scope of the present study.

Time profile. As shown in the correlational analysis, there is considerable within-unit consistency over the course of a day in income segregation. For many grid cells, however, the segregation level fluctuates hour by hour. Next, we use group-based trajectory analysis to find the latent groups in the daily fluctuation of income segregation. Table A1 in Appendix shows fit statistics under different model specifications. Based on BIC criteria (models with lower values preferred) and given the similarities between groups, we determine the optimal number of groups to be seven for both weekday (cubic) and weekend (quadratic)[4]. For weekday, the BIC value goes from 169,028.8 in the six-trajectory model with cubic specification to 166,885.0 in the seven-trajectory model with cubic specification. For weekend, the BIC goes from 165,230.1 in the six-trajectory model with quadratic specification to 162,994.8 in the seven-trajectory model with quadratic specification. We perform analyses using eight- and ten-trajectory specifications with linear, quadratic, and cubic terms. The additional trajectories emerge from

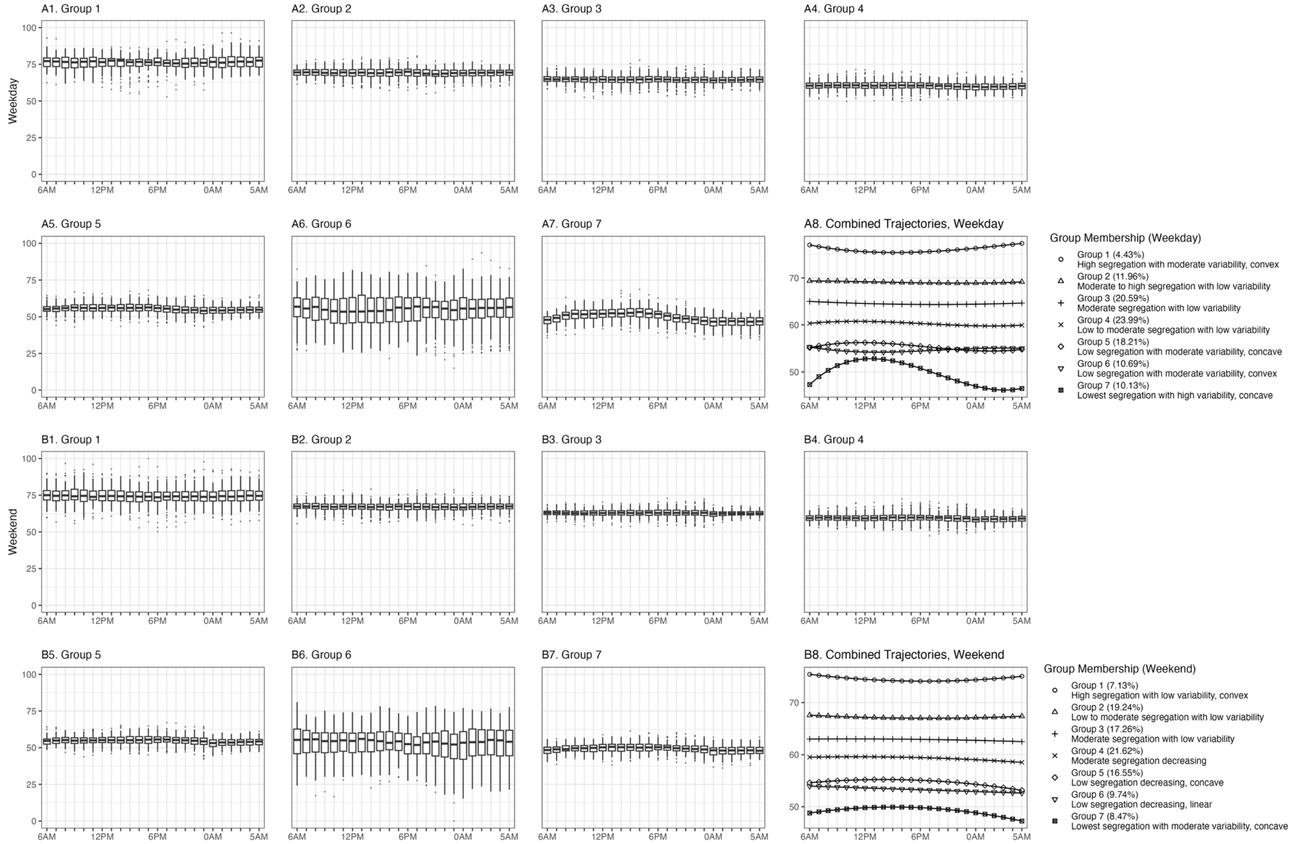

Fig. 4 Segregation trajectories around the clock. Unique trajectories of social segregation for each group with different income levels show varied variability throughout the 24 h on weekdays (**A1**–**A8**) and weekends (**B1**–**B8**).

the models are of small size (less than 5%) and do not meaningfully diverge from existing trajectories. We thus determine the optimal number of groups to be seven for both days. Figure 4 shows the common trajectories from group-based trajectory analysis. Panel A of Fig. 4 represents the seven distinct groups (A1–A7) and a combined trajectory plot (A8) for weekday; panel B includes individual group trajectories (B1–B7) and combined trajectories (B8) for weekend. The individual trajectories are visualized in boxplot to incorporate distribution information. Distributions are not included in the combined plots for better readability.

Weekday trajectories. Group 1, "high segregation with moderate variability, convex", represents 4.43% of the grids. Units in this group are characterized by consistently the highest level of segregation with a slight dip around noon. Group 2 ("moderate to high segregation with low variability"), Group 3 ("moderate segregation with low variability"), and Group 4 ("low to moderate segregation with low variability") are 11.96%, 20.59%, and 23.99% of the units, respectively. These three groups are all characterized by moderate levels of segregation and high consistency over the course of a day. Group 5 ("low segregation with moderate variability, concave", 18.21% grids) and Group 6 ("low segregation with moderate variability, convex", 10.69% grids) share a similar level of segregation throughout the day. Both groups start and end at a similar average level of segregation (Group 5: mean = 55.309, sd = 2.705; Group 6: mean = 55.681, sd = 10.978). While Group 5's segregation increases slightly during the day (around noon time) and decreases afterwards—thus exhibiting a concave trend, Group 6 shows the opposite (decreases during day and increases afterwards, convex). It should be noted, however, that Group 6 has the highest level of uncertainty in all trajectories, as shown in Fig. 4A6.

Group 7, "lowest segregation with high variability, concave", represents 10.13% of the grids. This group has the lowest overall segregation across 24 h and features high within-day velocity.

Weekend trajectories. Similarly, we identify seven unique trajectories for weekend income segregation. The trajectories are much like those on weekday, albeit with less overall variability. Approximately 7.13% grids belong to Group 1, "high segregation with low variability, convex." The overall segregation and variability in this trajectory are modestly lower than Group 1 in weekday. Like weekday trajectories, Group 2 ("low to moderate segregation with low variability", 19.24%), Group 3 ("moderate segregation with low variability", 17.26%), and Group 4 ("moderate segregation decreasing", 21.62%) all exhibit temporal stationarity, featuring moderate segregation and low changeability over the 24-h period. Again, Group 5 ("low segregation decreasing, concave", 16.55%) and Group 6 ("low segregation decreasing, linear", 9.74%) share a similar start and end level of segregation. The trajectory for Group 5 shows a downward concave trend. Group 6 departs from Group 5's pattern by showing a linearly decreasing trend. Last, Group 7, "lowest segregation with moderate variability, concave" is 8.47% of all weekend grids. In contrast to weekdays, Group 7 exhibits significantly reduced velocity on weekend.

Group membership transitions. The above analysis indicates that despite some variation, the overall trajectories and their distributions are similar across weekday and weekend. It remains unclear from this exercise, however, whether the same unit belong to the same group membership across the 2 days. We next investigate the extent to which units shift group membership. There is a moderately high consistency between the trajectories of

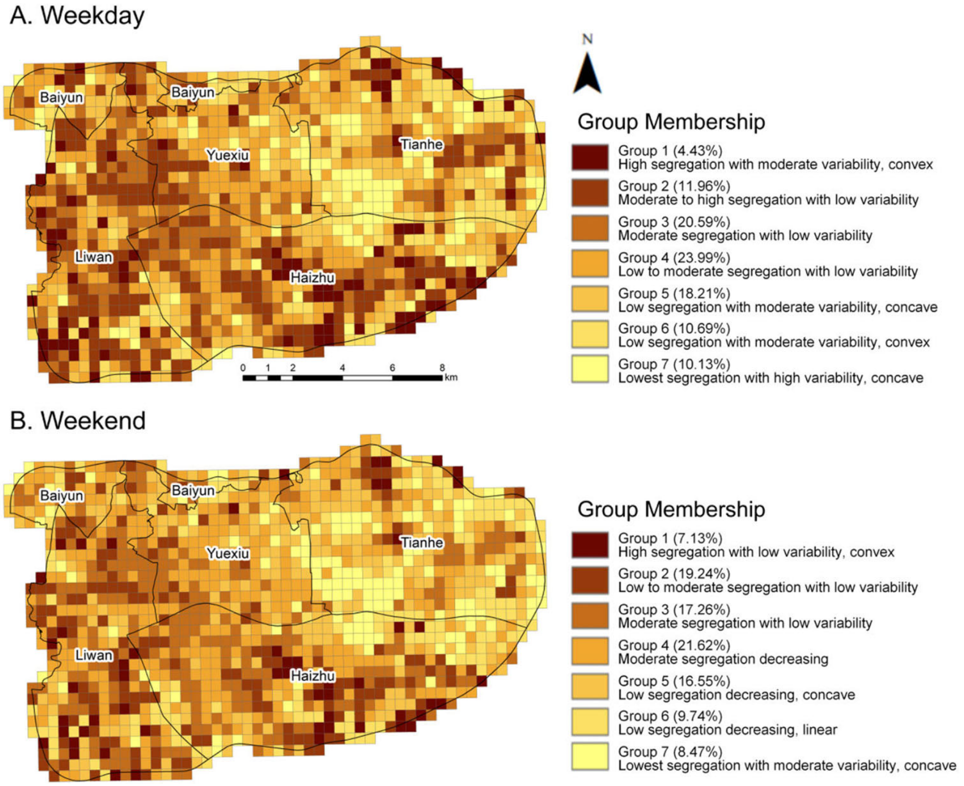

Fig. 5 Spatial distribution of segregation trajectory groups. The segregation trajectories of different income groups are varied in space on both weekdays (**A**) and weekends (**B**).

weekday and weekend (Cramer's $\Phi_c = 0.576$, $p < 0.001$). Figure A3 illustrates the transition between weekday and weekend's trajectories. As expected, most grids stay in the same groups during weekday and weekend (55.90%). In total, 34.28% grids stay in similar groups across the 2 days (e.g., Group 1 in weekday and Group 2 in weekend). Only less than 10% grids experience more drastic changes (e.g., Group 1 in weekday and Group 3 in weekend). This further highlights the temporal stability of the income profile in local geographic units. We then predict significant group membership shifts (i.e., group difference greater or equal to 2 and 3, respectively) with the same set of location and neighborhood predictors used in the location decomposition analysis. Results from multilevel logistic regression show that proximity to primary and middle schools, major shopping centers, and entertainment facilities is strongly negatively correlated with group membership shifts ($p < 0.05$). The share of non-local migrants is positively linked to significant shifts ($p < 0.05$). The presence of major transportation facilities is marginally positively related to meaningful shifts ($p < 0.1$). Details of the regression models are in Table A3 in Appendix.

Spatial distribution of trajectories. Figure 5 presents the geographic distribution of the clustered trajectories of units on weekday and weekend in central Guangzhou. Moderate to high segregation areas (Groups 1–3) are mainly distributed in the west and south part as well as the northeast edge of the central city. With large numbers of urban villages and the old town, these areas are dominated by low-income residents. CBD and its surrounding area emerge as areas with low segregation but relatively high hourly fluctuations (Group 5–7). Located in the east part of the central city, these newly developed areas feature more public open space and mixed land use, attracting large numbers of people regardless of income levels. With the ordered trajectories, we employ Moran's I statistics to quantify the degree of spatial patterning indicated in the maps. Group membership has a Moran's I value of 0.394 (z-value = 26.189, $p < 0.001$) on weekday and 0.378 (z-value = 26.238, $p < 0.001$) on weekend, meaning that there is non-trivial spatial clustering in the distribution of segregation trajectories.

We perform sensitivity analysis by replacing ordinal entropy with simple information theory entropy based on five income categories (with 1 and 2 collapsed into one low-income category and 6, 7, and 8 into high-income category for a less skewed distribution). Conclusions remain the same.

Discussion and conclusion

The intent of this study is to come to a better understanding of the temporal dynamics of segregation by income beyond the residential context. With large-scale granular mobile phone big data of a major Chinese metropolis, we explore how patterns of segregation among eight income groups unfold throughout the 24-h period on weekday and weekend. This study employs ordinal entropy, a metric suited for measuring segregation among ordered groups, to quantify the level of segregation of eight income groups at micro-geographic units.

We further our analysis by decomposing income segregation along the spatial and temporal dimensions. Spatially, we predict hourly segregation by different types of urban functions (transportation, institutions, residential, retail, accommodation, entertainment, and office) and neighborhood socio-demographic characteristics (number of residents and share of non-local migrants). We explore the role of these urban functions and socio-demographic characteristics in shaping the level and variability of income segregation and how the impact changes with time. Second, we delineate the time profile of income segregation by finding distinct trajectories in the segregation time series using group-based trajectory analysis. To do so, we investigate the unique types of trajectories, their stability across days (weekday and weekend), and their geographical distribution.

Three key findings emerge in our analysis. First, in line with prior research, our study confirms that social segregation fluctuates on a regular basis (Le Roux et al. 2017; Park and Kwan 2018) and varies between weekday and weekend (Zhang et al. 2022b). Due to massive and systematic commuting behavior on weekday, we observe higher overall variability in segregation on weekday than weekend, a finding previously noted in the literature (Zhang et al. 2022b). Our results also highlight that the degree of fluctuation varies among individual units, as the difference between the units with the highest and lowest variability is nearly 50-fold. Such differences are likely rooted in disparities in local social, economic, cultural conditions.

Second, the presence of daily urban functions and socio-demographic characteristics play a key role in shaping local income segregation and, more importantly, their impact exhibits significant temporal rhythm. Our regression analysis suggests that proximity to all kinds of retail facilities including supermarkets, wholesale markets, street markets, and shopping centers is associated with elevated levels of income segregation. Being located most often near major residential areas, the constant segregation-prompting effect of supermarkets reflects the income-stratified housing market. Similarly, the location of wholesale markets, which cover a large land area, are typically near the city limit or in suburbs. Unlike the West, wholesale markets in China are primarily designed for and cater to retailers, which implies that frequent visitors are likely to be highly structured by their income level. This in turn is linked to an increased level of income segregation in areas with wholesale markets. Street markets, due to its spatial and temporal characteristics (set up informally near residential space on weekend) and target population (appeal mostly to population of lower income for lower prices), is significantly related to income segregation only during daytime on weekend. By contrast, major shopping centers, which attract economically better-off individuals and families, exhibit a strong positive relationship with segregation around their opening hours. The presence of accommodations is linked to reduced income segregation on weekday and less consistently on weekend. As a popular tourist destination, the City of Guangzhou, particularly within its urban core, hosts a vast number of business and leisure travelers from diverse socio-economic backgrounds. This is largely due to its easily accessible public transportation and numerous opportunities available. Thus, having accommodations with a large price range lowers local income segregation. Last, the presence of office spaces represents greater job opportunities. Through facilitating social heterogenization during daytime, office spaces, therefore, significantly limit income segregation during daytime, a finding well documented in the literature (Ellis et al. 2004; Hall et al. 2019; Le Roux et al. 2017). We also demonstrate that, except for a few locations such as supermarket and wholesale market, most locations and neighborhood contextual features have a clear temporal rhythm. Some are directly linked to their operating hours while others shape (and are shaped by) segregation in more complex and nuanced ways. Our variability analysis illustrates that certain types of urban functions may encourage fluctuations in the local social environment, while others may constrain changes and stabilize the local social ecology. Future studies are encouraged to examine more systematically and causally how urban functions contribute to segregation.

Regarding neighborhood context, we find that the number of residents positively predicts income segregation during daytime (10 a.m.–4 p.m.) on weekday, which is in line with employment dynamics. Areas with denser population likely also have greater abundance of opportunities. During commute time, people are drawn into places more resourced, typically of a high population density. And opportunities are not randomly distributed geographically but instead structured or even dictated by local resources (e.g., job, leisure, institutional), thus making population of certain backgrounds more concentrated in the local area. During weekend, this correlation is extended later to midnight. This reflects the longer lingering of residents around home, making more extensive use of local resources. The share of non-local migrants is positively correlated with income segregation on weekday night (9 p.m.–7 a.m.) and weekend night through morning (9 p.m.–10 a.m.). The pattern echoes migrants' employment spatiotemporal dynamics. Facing relatively worse socio-economic conditions, non-local migrants largely dwell in low-cost urban villages and suburbs. They are drawn out of their home space during working hours, thus alleviating the segregation-increasing impact of migrant concentration. As they return home during the night, income segregation significantly intensifies due to the homogeneity of migrants' income profile. The extended impact of the factor on weekend captures the longer lingering time on weekend among non-local migrants.

To our knowledge, this is the first study to quantitatively examined how local urban functions and neighborhood context dynamically shape segregation around the clock. We argue that temporally unpacking the role of local institutions, facilities, and neighborhood context is a crucial step toward an understanding of dynamic ecology at micro-geographic units. It is at the micro units that social contacts and segregation are experienced. Depending on the geographical and temporal arrangement of institutions and facilities, physical and social characteristics of the environment, availability of public and private services, socio-cultural features, and even reputation may show non-trivial amount of temporal variation throughout the day (Macintyre et al. 2002; Vallée 2017). Such temporal variations are consequential for health, safety, and well-being among local residents, employees, and visitors (Boessen et al. 2017; Jacobs 1961; Neutens et al. 2010; Zhang et al. 2022a). Our findings shed light on how income segregation varies over 24 h and how it covaries with local urban functions and neighborhood context. With more nuanced temporally varied policy and urban design, policy makers and urban planners may more effectively fight increasing social and racial segregation across the globe. Caution should be made, however, that segregation is multidimensional and reducing segregation in one dimension may unexpectedly promote segregation along other dimensions.

Third, like Le Roux et al. (2017) and Zhang et al. (2022b), we find that the seemingly convoluted and individualistic 24-h social segregation time series follow only a handful of distinct trajectories. Based on common trend characteristics of income segregation, we further our analysis by grouping the segregation trends of micro units into seven clusters using group-based trajectory analysis for weekday and with some adjustments seven similar clusters for weekend. A noticeable pattern that emerges from our grouping analysis is that most trajectories are categorically defined by their starting segregation level and remain relatively stationary throughout the day (Groups 1–4 on weekday and Groups 1–4 and 7 on weekend). This is also indicated in the moderate to high correlation of ordinal entropy values within each day and between the two sampled days. Further, with transition analysis, we reveal that less than 10% of units experience meaningful shifts between groups from weekday to weekend. Much like local crime (Sampson 2012; Weisburd et al. 2012), segregation level is relatively "sticky" over time, both in the short and long timeframe, and the level of segregation is a defining and enduring characteristic of micro units. Significant changes are observed in only a handful of urban grids, where there is a greater degree of population heterogenization over time. While much lower than residential segregation (Le Roux et al. 2017; Zhang et al. 2022a) and possibly less "sticky" than residential segregation, segregation in the ambient population is likely also deeply rooted in local institutional resources, urban functions, and neighborhood composition that encourage or discourage population mobility. Our finding intimate that the durably high or low levels of income segregation throughout the day may have fueled high or low levels of segregation in the long run. Our results also indicate that, on an hourly basis, individual residents and other frequenters are consistently exposed to similar levels of contextual conditions, highlighting the real-time channel of neighborhood effect in shaping individual well-being. We hope our analysis can inspire future research in this avenue.

These findings have several policy implications. First, policy should attend not only to the spatial distribution of income segregation but also to its temporal dynamics. A key focus should be placed on urban functions. Urban functions such as supermarkets and wholesale markets exhibit constant segregation-increasing effect. This could be due to the location choice of such retailers in the first place to cater to certain income groups. Over time, these places may draw people of similar income profile, thereby further functioning as an isolation force. Urban planners could consider, for example, breaking this reinforcement loop by introducing facilities that bring people of diverse backgrounds together (e.g., accommodations and offices). In addition, instead of concentrating homogeneous retailers in the same space, retail agglomeration could focus on offering diverse products in a single shopping trip. Second, our variability and transition analysis suggest that institutions and urban land use may limit the overall variability of segregation and its trajectory. In line with the New Urbanist approach, designing mixed urban land use may facilitate not only street surveillance abilities but also urban vitality (Kitchen 2005). By bringing urban spaces into the activity spaces and subsequently awareness space and housing choice set of diverse groups, a more diversified housing market may become possible (Krysan and Crowder 2017). Third, despite being in constant change, the trajectory of income segregation is more decisively shaped by the initial level, meaning that short-term fluctuations of population composition may also have their roots in the structural differences across spatial units. Policies targeted at reducing short-term segregation (e.g., relocating the homeless), therefore, may be less effective. Segregation and other characteristics may easily revert to the status quo as long as the structural conditions remain unchanged.

There are a few limitations that this study introduces. First, having different groups of people in the same physical space does not automatically lead to social contact between them (Xu 2021). Ethnographers have long observed how individuals carefully avoid interactions that cross the border of race and class through subtle visual cues (eye work) and deliberate self-isolation, even when they are in close physical proximity (Anderson 2011). Second, people who are not co-present in the same physical space may still have significant social contact in the virtual space. Given the increasing importance of virtual contact in the post-pandemic world, future studies could examine segregation in non-physical social interactions. In addition, unequal access to and ability to adapt to remote working and online shopping may further exacerbate income-based segregation. We encourage future work on investigating how post-pandemic new norms translate into segregation in the physical space. Third, our findings pertaining how urban functions influences the fluctuations of income segregation is correlational. Future studies could examine the causal relationship between the two by harnessing methods such as quasi-experiments (e.g., how the closure or opening of stores and related policy changes affect local segregation levels). In addition, the observation period of this study is relatively short. Arguably, individual mobility is dictated by high regularity; the 2-day observation period should provide sufficient insights into how segregation fluctuates at the population level.[5] Future studies could look into changes in segregation over a longer period (e.g., week, seasonal and annual changes) and how special events (e.g., major holidays) may affect patterns of segregation. Moreover, this study examines the segregation patterns of weekday and weekend separately. Future studies could explore the interconnection between weekday trajectories and weekend trajectories given that many day-to-day institutions have clear weekday-weekend rhythms (e.g., schools, churches, amusement parks). Furthermore, the data used in the study may be subject to various types of biases and errors. For example, the aggregation process from individual devices to grid cells on an hourly basis may involve errors such as dropped stays less than 30 min. Moreover, the income groups in the ambient population are classified by the data provider using their patented classification algorithm, which is beyond the control of researchers. However, given that their classification is based on multiple consumption indicators—ranging from phone bills to inter-city travel behaviors—rather than one single indicator, we believe that this classification reasonably captures people's economic well-being and is less susceptible to the noise associated with any single indicator. Nevertheless, it should also be noted that our big mobile phone dataset is still the state-of-the-art mobility dataset available in the City of Guangzhou and is preferred over traditional datasets (e.g., surveys). The dataset has a much wider geographic, temporal, and population coverage during the study period. In addition, we focus on the central urban areas within the city ring expressway of a major metropolis, which may limit the generalizability of our results to non-urban areas or smaller urban areas. Last, while the big mobile phone data employed in this study cover a wide range of population in the urban core of Guangzhou, there are a few population groups (e.g., seniors and children) that are underrepresented due to the lower prevalence of mobile phones. Considering that the vulnerable groups are probably less mobile and disproportionately subject to contextual effects (Minh et al. 2017; York Cornwell and Cagney 2017) including the local rhythms of segregation, we recommend that future studies specifically target the underrepresented groups in the era of massive location data. However, due to the relatively small proportion of these population groups, it is anticipated that our main results will likely remain consistent even with the inclusion of these subgroups. Relatedly, individual differences in phone usages may also have an impact on our dataset, capturing the digital traces of certain types of individuals more accurately than others (Cagney et al. 2020).

Data availability

Due to the requirements of the telecommunications company, the data used in this paper is confidential.

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Notes

1 A person is registered to a grid cell for the hour if and only if the individual/device stays for at least 30 min within the cell. A person/device can be counted in a maximum of two cells per hour.

2 In the literature, studies usually collapse the continuous or ordinal information into a few groups when employing this technique, thus running the risk of substantial information loss.

3 The rank-order entropy index extends the standard ordinal entropy index by estimating a polynomial function based on the segregation curve across the income

distribution. In the present study, we have eight ordinal categories as our income groups. These groups, however, do not have the precision for an estimation of the income distribution.

4 While the BIC statistic favors 8 groups over 7 groups in our analysis, the additional group identified are not meaningfully different from existing groups.

5 We performed additional analysis by comparing the hourly ambient population on two study days with the monthly averages for all weekdays and weekends in October 2019 and October 2020, respectively. The Pearson's correlation coefficients range between 0.882 and 0.906 for the weekday (June 10th, 2020) and between 0.888 and 0.917 for the weekend day (June 13th, 2020).

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Author contributions
All authors contributed significantly to this article and approved the submitted version. Liang Cai: conceptualization, formal analysis, model calculation and writing. Guangwen Song: data collection, mapping, writing and reviewing. Yanji Zhang: supervision, writing, reviewing and editing.

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This article does not contain any studies with human participants performed by any of the authors.

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