DISENTANGLING INDIVIDUAL-LEVEL FROM LOCATION-BASED INCOME UNCOVERS SOCIOECONOMIC PREFERENTIAL MOBILITY AND IMPACTS SEGREGATION ESTIMATES

COMPLEXITY72H

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June 28, 2024

ABSTRACT

Segregation encodes information about society, such as social cohesion, mixing, and inequality. However, past and current studies often tackle socioeconomic (SE) segregation by analyzing static aggregated mobility networks, without considering further individual features beyond income and, most importantly, without distinguishing individuals from location-based income. Accessing individual-level income may help mapping macroscopic behavior into more granular mobility patterns, hence impacting segregation estimates. Here we combine a mobile phone dataset of daily mobility flows across Spanish districts stratified and adjusted by age, gender and income with census data of districts median income. We build mobility-based SE assortativity matrices for multiple demographics and observe mobility patterns of three income groups with respect to location-based SE classes. We find that SE assortativity differs when isolating the mobility of specific income groups: we see that groups prefer to visit areas with higher average income than their own, which we call preferential mobility. Our analysis suggests substantial differences between weekdays and weekends SE assortativity by age class, with weekends characterized by higher SE assortativity. Our modeling approach shows that the radiation model, which typically performs best at reproducing inter-municipal population mobility, best fits middle income and middle-aged flows, while performing worse on young and low income groups. Our double-sided approach, focusing on assortativity patterns and mobility modeling, suggests that state of the art mobility models fail at capturing preferential mobility behavior. Overall, our work indicates that mobility models considering the interplay of SE preferential behavior, age and gender gaps may sensibly improve the state of the art models performance.

Keywords Mobility · Networks · Segregation

Introduction

Spatial and social segregation in living spaces has been shown to have a significant impact on daily life of residents Massey and Denton [1988]. Such segregation is often based on factors such as income, gender, ethnicity and age, and can dictate where people live, work and conduct their day-to-day activities Schelling [1969], Zhang et al. [2019].

Social factors, in turn, can directly and indirectly lead to affect access to healthcare and education, emphasizing social, economic, political and health disparities Hu et al. [2022], Li et al. [2022a].

The study of segregation in living spaces has evolved significantly over the years, incorporating various aspects of human mobility. Traditional approaches focused mainly on residential segregation, assigning socioeconomic characteristics to individuals based on their home locations Liao et al. [2024]. However, recent research has highlighted that mobility patterns play a crucial role for a more comprehensive understanding of spatial and social segregation Moro et al. [2021], Athey et al. [2021]. Studies have demonstrated that incorporating social aspects such as income, age, gender and ethnicity into mobility patterns analysis can either reduce or amplify spatial and social segregation Moro et al. [2021], Liao et al. [2024]. For instance, income segregation has been associated with differences in place and social exploration. Moreover, segregation estimates may change whether integration is measured on aggregate or individual levels.

Wealthy groups tend to travel longer distances Farber et al. [2015], Barbosa et al. [2021], Li et al. [2022b], while less affluent groups tend to make shorter trips Wu and Huang [2022]. Gender also plays a significant role in mobility patterns, with women traveling more frequently, for shorter distances with multiple stop points and preferring public transport compared to men Law [1999], Acker [2018], Gauvin et al. [2020]. As noted by Cresswell and Uteng [2016], "how people move (where, how fast, how often) is demonstratively gendered". Similarly, mobility patterns differ across age groups, beyond gender and income Lenormand et al. [2015], yielding a further level of complexity when it comes to intersectional groups. Moreover, women with lower socioeconomic status tend to walk more while women with higher socioeconomic status, education tend to commute using bicycle more Yuan et al. [2023].

Despite these advances in understanding segregation, several challenges remain in capturing the complexity of the interplay of demographic groups mobility patterns and segregation.

1. Dynamic nature of segregation: Many studies focus on static networks, overlooking potential differences that may occur on a daily scale, such as between weekdays and weekends Nilforoshan et al. [2023].
2. Interplay of individual and local income: most studies assign individuals' SE statuses based on their home-place income, however the interplay of individual income with location income may play an important role on mobility patterns and on SE segregation.
3. Multidimensional segregation: The interplay between various demographic factors in shaping mobility patterns is not fully understood Bokányi et al. [2021].
4. Limitations of current human mobility models: population mobility models typically overlook the behavior of demographic groups and the role of different mobility purposes in shaping mobility pattern Zhao et al. [2023].

To address these challenges, here we leverage a public dataset of mobile phone records released by the Spanish Ministry of Transport, Mobility and Urban Agenda of Spain, *MITMA*Ministry of Transport, Mobility and Urban Agenda of Spain, MITMA [2024], encoding daily scale trips across Spanish districts stratified by age, gender and income of individuals, and study how segregation varies across demographic groups day by day. We cross these data with official data on median income provided by the Spanish National Statistical Office Instituto Nacional de Estadística, INE [2024], to map population mobility into ten location-based SE classes. We analyze how individuals of a given income class behave with respect to their home location in visitation patterns from home to destinations classified by mobility purpose (work/study, frequent and non-frequent destinations). Mobile phone data are crucial to inform transportation planning and public health research Murray et al. [2020], Badr et al. [2020], Xiong et al. [2020], Grantz et al. [2020]. In transportation, these data enable the analysis of travel patterns and mobility flows Xu and Zhao [2022], traffic congestion and network performances Essadeq and Janik [2021], impact of emergencies and events ESCAP [2022] thus helping in effective transportation planning, traffic management, emergency responses to name a few. In public health, mobile phone data help in identifying and tracking the drivers of transmission Murray et al. [2020], estimating the exposure to environmental hazards Hatchett et al. [2021], aiding contact tracing Ming et al. [2020], Jahnel et al. [2020], assessing the risk of virus importation from different regions, and informing public health policies Grantz et al. [2020].

Finally we dive into mobility modeling and assess what is the level of agreement of a common state of the art model, i.e. the radiation model, at capturing mobility patterns of the various demographic groups. We find that the best agreement between modeled and observed trips is with middle income and middle-age groups, highlighting how this population mobility model does non perform well at reproducing mobility of low income, young age class demographic groups, especially for out-of-routine mobility.

Our work suggests that considering both individual and location-based income information when studying mobility patterns impacts socioeconomic segregation estimates and suggests that population mobility behaviors are not only explained by population spatial distribution and distance, but also by destinations income. Moreover, adding SE information may help building new mobility models, helping increasing models performance, improving human mobility estimates in data desert regions, and better informing epidemic models for public health policies.

Methods

Data

We use mobile phone data collected by a national mobile network operator in Spain Ponce-de Leon et al. [2021], and published by the Ministry of Transport, Mobility and Urban Agenda of Spain, *MITMA* in a public online repository Ministry of Transport, Mobility and Urban Agenda of Spain, MITMA [2024]. The data describe the hourly movements of individuals between Spanish districts from January 2022 to May 2024. Original districts defined by Spanish National Statistical Office (INE) are mapped into a coarser spatial division in which small districts with low population density are grouped to include areas not covered by antennas Ponce-de Leon et al. [2021], resulting in 3792 districts. The trips were aggregated using users' movements between consecutive *stays* of at least 20 minutes in the same area, disregarding trips of less than 500 meters Ponce-de Leon et al. [2021]. The data is aggregated in terms of origin-destination (OD) matrices at hourly time scale, encoding trips occurred during a given hour between two districts. Individuals belong to a given age-range (e.g. $0-25$, $25-45$, $45-65$, $65-100$ years), gender (e.g. female, male) and income (e.g. <10, $10-15$, >15 thousands euros per year) class. For some routes, users' features have been anonymized to ensure privacy. For each origin and destination, the activities at origin and destination are classified as home, work/study place, frequently and infrequently visited place. This data collection is based on individuals' active events, e.g., users' calls together with passive events, in which the user's device position is registered due to changes in the cell tower of connection. For the districts level distribution of income, we rely on the median income by consumption unit released by the Spanish National Statistical Office Instituto Nacional de Estadística, INE [2024].

Assortativity

At the socioeconomic (SE) level of aggregation, we define *assortativity matrices* X between income deciles D for each SE class, following the approach in Bokányi et al. [2021]. Here, we used the probability of a subgroup of people living in income decile $D=i$ to commute to a district with income decile $D=j$ to work or study.

$$C_{ij} = \frac{\sum_{\{u\in U | D_{u,home=j}, D_{u,work=i}\}} 1}{\sum_{\{u\in U | D_{u,home=j}\}} 1}$$

Given the normalized assortativity matrices $\tilde{X}$, we compute the *assortativity* with the Pearson correlation coefficient of the matrix entries, across all income deciles. A completely assortative matrix will have assortativity of value 1.

$$\rho_X = \frac{\sum_{i,j} ij\tilde{X}_{ij} - \sum_{i,j} i\tilde{X}_{ij} \sum_{i,j} j\tilde{X}_{ij}}{\sqrt{\sum_{i,j} i_{ij}^2 - (\sum_{i,j} i\tilde{X}_{ij})^2}\sqrt{\sum_{i,j} j_{ij}^2 - (\sim_{i,j} j\tilde{X}_{ij})^2}}$$

Socioeconomic Preferential Mobility Index

We introduce the *socioeconomic preferential mobility index* to better understand how individuals are moving between socioeconomic districts. Here, by computing the probability of moving from one SE class to another, we can compare the amount of flows towards richer SE classes with respect to those bound towards poorer SE classes.

$$R = \frac{S_{upper} - S_{lower}}{S_{upper} + S_{lower}},$$

where S_{lower} is the sum of the elements in the lower triangular matrix, i.e. towards lower SE classes and S_{upper} the sum of the elements in the upper triangular matrix, i.e. towards higher SE classes, both without considering the matrix diagonal. The index will be $R=1$ if no trips occur towards lower SE classes and $R=-1$ if no trips occur towards higher SE classes, whereas $R=0$ if the two amounts of trips are equally balanced.

Mobility modeling

We model flows between districts using a *radiation model*. This model captures complex patterns and performs better than traditional gravity models, especially for travel over long distances Simini et al. [2012]. The model is specified as

$$T_{pq} = O_i \frac{1}{1-\frac{m_p}{M}} \frac{m_p m_q}{(m_p + s_{pq})(m_p + m_q + s_{pq})}, \tag{1}$$

where T_{pq} is the average number of travelers from location p to q, O_p is the number of trips originating in p, m_p and m_q are the number of opportunities (here represented by population) at the origin and destination respectively, s_{pq} is the

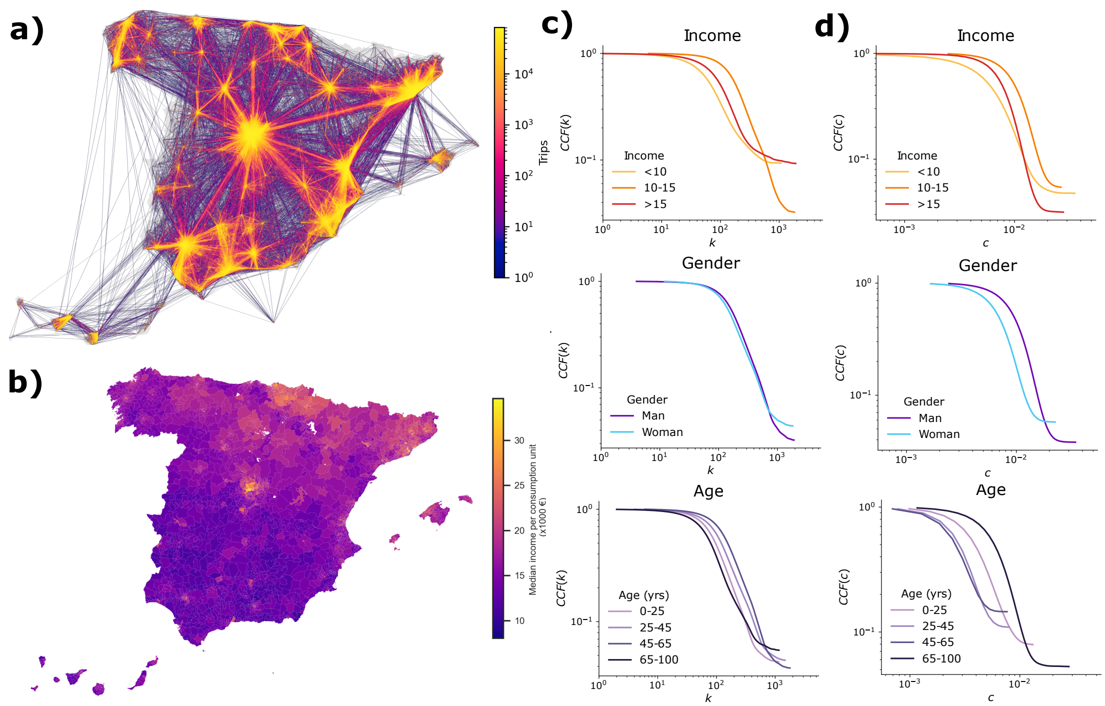

Figure 1: **Mobility and median income across Spain a)** Mobility network between Spanish districts. Districts are represented as nodes, connected by the normalized number of trips between them for the first week of September 2023, in log scale. **b)** Heatmap of median revenue per consumption unit of Spanish districts. **c)** Degree complementary cumulative density function (CCF) by income class, gender and age. The degree represents the number of unique districts visited by travelers of each district. **d)** The complementary cumulative density function (CCF) of the local clustering coefficient is analyzed by income class, gender, and age for each district.

number of opportunities (i.e. population) within a circle of radius r_{pq} centered at p (excluding source and destination), and $M = \sum_p m_q$ is the total number of opportunities. The model assumes that travelers choose destinations based on the quality of opportunities, represented by a fitness value z drawn from a distribution $P(z)$. A traveler selects the closest opportunity with a fitness exceeding their threshold, also drawn from $P(z)$.

We also compare the observed mobility patterns with the results of the radiation model to understand the structural biases in geography of Spanish mobility.

Results

Spatial mobility

Our analysis focuses on the spatial patterns of inter-district flows and economic indicators in Spain. Fig.1 illustrates key findings from our study. **Inter-district flows**: Figure 1a depicts the normalized amount of flows between Spanish districts on a logarithmic scale. The data represents trips recorded over a one-week period starting from the first of September, 2023. **Economic disparities**: The median revenue by district is shown in Fig.1b. A clear north-south gradient is observable, with districts in the northern regions and in city centers generally exhibiting higher levels of wealth.This pattern indicates a significant level of economic disparity across the countries geography. **Spatial auto-correlation of income**: To quantify the spatial relationship of income distribution, we calculated the Moran's Index Rey and Anselin [2009], Cliff and Ord. [1981]. Our calculations returned a value of 0.73 indicating a strong and significant spatial auto-correlation. This high value suggests that neighboring districts tend to have similar income levels, further reinforcing the observed geographical economic divide.

Network and spatial properties To better understand the mobility patterns across income, gender and age we conducted a descriptive statistic analysis of the mobility network during the first week of September 2023. The complementary cumulative function (CCF) based on degree k and local clustering coefficient c are shown in Fig.1c and d, respectively. The degree represents the number of unique districts visited by travelers from each district, categorized by income, gender and age groups.

The degree distribution $CCF(k)$ reveals several key findings: (1) Middle-income travelers (10-15 thousand euros per year) exhibit the most extensive connectivity, visiting the widest range of unique places. This is evidenced by a later and more gradual decline in their distribution. Low-income travelers (<10 thousand euros per year) show a sharp and early decline in their degree distribution, indicating they visit fewer unique places. This pattern may be attributed to financial constraints limiting their mobility. High-income travelers (>15 thousand euros per year) demonstrate a slightly delayed decrease compared to the lower-income group. This suggests that wealthier individuals tend to visit more unique places than low-income travelers, but not as many as the middle-income group. (2) Gender-group analysis reveals that men show a slightly later decline in $CCF(k)$ compared to women, indicating a marginally greater number of unique places visited by men. (3) Age-group mobility patterns show the highest degree of connectivity and largest range of places visited in the middle-age groups (25-45 and 45-64 years). Their degree distributions decline gradually and less steeply compared to other groups. The eldest (65-100 years) and the youngest (0-25 years) age groups exhibit sharper and earlier declines in their degree distributions, indicating more constrained mobility patterns.

The local clustering distribution $CCF(k)$ weighted by the trips Saramäki et al. [2007], highlights the integration level of the network of visited districts for different traveler groups. This measure provides insights into how interconnected the travel patterns are for various demographic segments. (1) High-income travelers demonstrate a more homogeneous pattern, indicating consistent mobility patterns that likely reflect well-established social structures in frequented locations. While the middle-income group exhibits more variability with a wider range of mobility patterns and social interactions. On the other hand, the low-income group shows a rapid decrease in the inter-connectedness of districts, reflecting limited mobility and lower levels of social integration. (2) Gender-group analysis reveals that on an average women exhibit a slower and more gradual decline in $CCF(k)$, indicating greater homogeneity in their mobility patterns. The overall inter-connectedness for women is lower, highlighting different social network structures and travel behaviors between genders. (3) Age-group mobility patterns indicate that the youngest (0-25 years) and eldest age group (65-100 years) show broader and more interconnected networks than the middle-aged groups (25-45 and 45-65 years), which can be related to less varied location visits and a more stable set of frequented places.

These patterns further demonstrate that economic capabilities and social inclinations can give an intuition on the different pattern of mobility.

Assortativity and segregation analysis

To uncover the level of segregation in mobility, we use two coefficients: we employ the known ρ assortativity Bokányi et al. [2021] and introduce the R Socioeconomic Mobility Preference Index. The assortativity being a measure of segregation across all the SE classes. The socioeconomic preferential mobility index representing the overall tendency of segregation of the income group.

The assortativity matrices in Fig. 2a illustrate the variations in travel patterns among the three income groups (<10, 10-15, >15 thousands euros per year). When considering the overall amount of trips, individuals from poorer classes frequently visit richer districts, while those from wealthier areas tend to travel often to poorer districts. The middle income group exhibits a more uniform distribution of mobility across middle-class districts, resulting in a notably higher assortativity coefficient. This indicates a greater correlation within the assortativity matrix and more segregated mobility patterns.

To examine potential mobility biases towards different income groups, we introduce a new metric, the Socioeconomic Preferential Mobility Index R, which quantifies the preference for moving from one's home to districts of higher or lower income levels for each income class. The probability matrices in Fig. 2b demonstrate that, after normalizing mobility by the home district's socioeconomic status, all income groups show a tendency to travel more frequently towards the wealthiest districts. The mobility bias is most pronounced among the lowest income group and diminishes progressively with increasing income.

Fig. 2c reveals the dynamics of assortativity ρ in September 2023 across different genderes and age groups. The trend exhibits a weekly regularity, without systematic differences from one week to the next. Only weekends showing higher levels of assortativity compared to weekdays, meaning higher level of segregation during weekends. Additionally, there is a significant difference in assortativity levels among the oldest individuals, with men particularly displaying higher assortativity than women.

Fig. 2d illustrates the dynamics of the Socioeconomic Preferential Mobility Index R in September 2023 across different genderes and income groups, aggregated by weekday. The aggregation is done due to the weekly regularity of assortativity temporal trends, and to minimize noise due to multiple layers of stratification. Consistent with the patterns

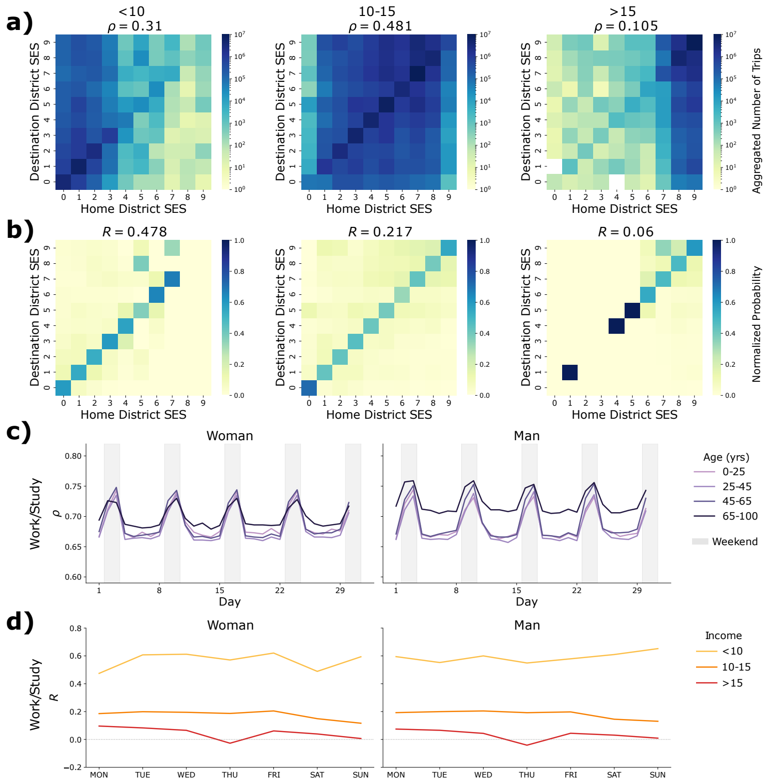

Figure 2: **Assortativity ρ and Socioeconomic Preferential Mobility Index R a)** Assortativity matrices aggregated over a working week from 4-8 September 2023 across three income groups (<10, 10-15, >15 thousands euros per year). **b)** Probability matrices (normalized by Home District SES) aggregated over a working week from 4-8 September 2023 across three income groups (<10, 10-15, >15 thousands euros per year). **c)** Assortativity ρ dynamics for travels from home to work or studying in September 2023 among different genderes and age groups (0-25, 25-45, 45-65, 65-100 years). **d)** Socioeconomic Mobility Preference Index R aggregated by weekdays for travels from home to work or studying in September 2023 among different genderes and income groups (<10, 10-15, >15 thousands euros per year).

observed in the probability matrices in Fig2b, individuals from the lowest income group exhibit a consistently higher mobility preference towards the wealthiest districts. The same trend is present among middle-income groups, although to a lesser extent, and it diminishes further among the richest individuals. This effect remains consistent across all weekdays.

Radiation model simulation

Mobility decays with distance in the data: districts that are closer in space have a higher likelihood of trips between them. Fig. 3a shows this decay for all trips and then disaggregated by mobility purpose, showing that infrequent trips typically reach farther distances than frequent trips and commutes. We see a kink in the cumulative distribution at a distance that corresponds to the width of the Iberian peninsula, suggesting that trips between mainland Spain and its islands exist off this decay function. This logic of distance decay allows us to implement the radiation model, which uses just population spatial distribution and distance to predict flows between areas.

We use two measures to evaluate our model, common part of commuters and fitted slope. We use the Sørenson-Dice index, also called Common Part of Commuters (CPC) in the study of mobility Barbosa et al. [2018], to measure goodness-of-fit. This measure quantifies the similarity between the magnitude of observed and predicted flows and always lies within the interval [0, 1], with 1 indicating a perfect agreement between all predictions and observations and 0 indicating total disagreement at all links in the network. Our results are comparable to other models in a variety of contexts Lenormand and Samaniego [2023], Simini et al. [2021], Cabanas-Tirapu et al. [2023], despite fitting no free parameters and simulating a resolved spatial scale. We achieve a CPC above 0.5 for all trip purposes and all socioeconomic classes. Our dataset enables us to understand how model performance varies for different groups and different kinds of trip, which should inform future work in mobility prediction. Disaggregating the results in Fig. 3b,

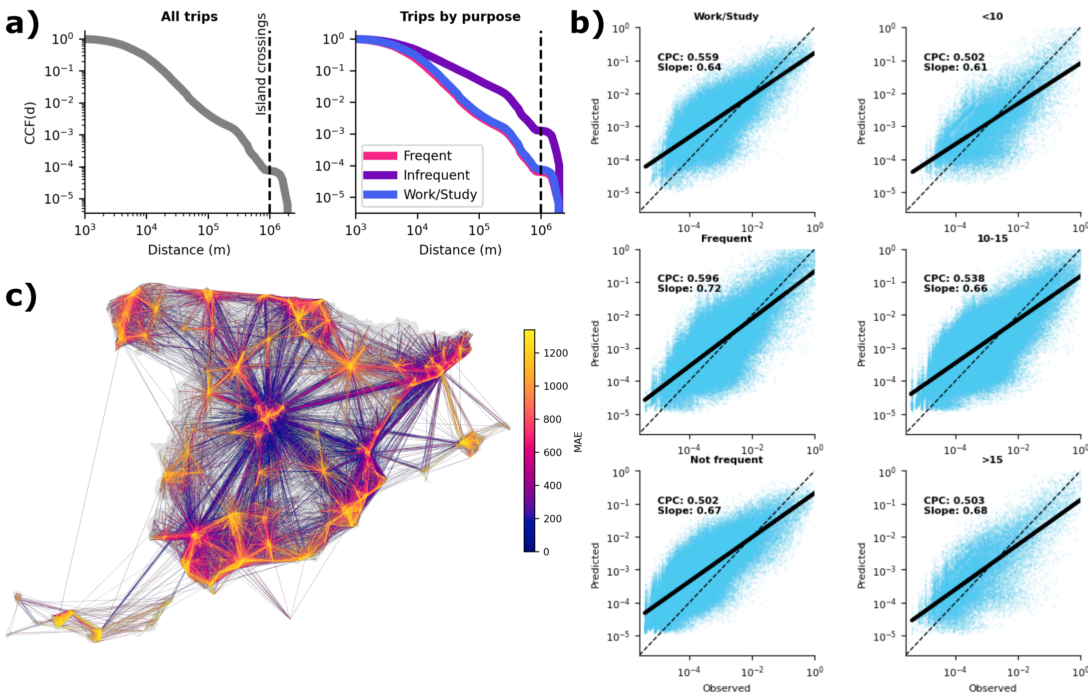

Figure 3: **Radiation model of mobility a)** Trip frequencies decay with distance, with a plateau representing trips that go further than the Iberian peninsula and thus cross to the islands. **b)** Comparison of mobility flows observed and predicted by the radiation model, stratified by mobility purpose and income group. CPC stands for the common part of commuters. **c)** Resulting mobility network capturing the mean absolute percentage error for all links in original network, clear colors representing big errors, darker colors representing small errors.

the radiation model best approximates trips to frequented locations and trips by the middle income bucket. Surprisingly, the model does not perform best on work/study trips, since the radiation model is intended to model commuting and internal migration patterns rather than out-of-routine and frequent non-commuting day-to-day travel. This suggests that model evaluations employed in other work may be obscuring heterogeneous performance across different groups.

Because of CPC's limitations, we also look at the slope, which tells us how close the radiation modelled travel probabilities are to the observed ones, with 1 being a perfect fit. Here we see again that frequent activities fall closest to this ideal but the results for income groups are mixed: the middle and high income groups are similar.

Not only is the model performance heterogeneous across trip characteristics, it is also spatially variable, which we see in Fig. 3c: the model performs best predicting long journeys—especially between Madrid and peripheral cities, but it struggles to predict trips for low populated areas around Madrid and in peripheral provinces. As the distance decay would suggest, the model also does not perform well in the islands, where some of the highest error are. Spanish provinces around Madrid and in the coast are less populated so the model is also fitting flows between sparse and dense areas but erring with flows between sparse areas.

Discussion

This study highlights important issues in the study of human mobility and estimation of segregation by using a rich dataset that disaggregates trips by socioeconomic class, gender and age, avoiding problems with income imputation common in other work. Accessing individual-level income may help mapping macroscopic behavior into more granular mobility patterns, hence impacting segregation estimates.

Key network characteristics like clustering coefficient and degree show substantial differences when we analyze the network according to these dimensions, showing that economic capabilities and social inclinations can give an intuition on different pattern of mobility.

Since individual-level income flows seem to be biased with respect to the destination income, we introduced a measure of preference in mobility with respect to destination income, capturing the asymmetry between upper and lower triangles of the assortativity matrix. This metric tells us whether the mobility of population residing in given districts SE classes are systematically biased towards higher or lower destination SE classes, encoding the unbalance of mobility flowing predominately towards lower or higher deciles districts. The bias index builds on studies of mobility assortativity Napoli et al. [2023], Bokányi et al. [2021], but shedding line on the direction of sorting.

With respect to our assessment of asymmetries in the assortativity matrix, previous work has found that while mobility is assortative, mixing tends to be driven by lower classes mixing with higher ones rather the opposite Bokányi et al. [2021], Noulas et al. [2012]. We confirm these findings in this context, however by disaggregating by individual-level rather than location-based SE class we observe additional layer of complexity: in general, people mobility is biased towards wealthier areas with respect to their home location SE class.

We show here that trip category and individual characteristics also matter when modeling aggregated origin-destination matrices. Our modeling approach, employing a radiation model, shows that performance varies across demographic groups, performing best for frequent routine mobility and middle income classes. This suggests that current models may be unsuited for capturing mobility of specific groups, e.g. lowest income class, and to explain specific mobility purposes, like infrequent activities. We observed a separate distance decay function for infrequent trips, which may explain the scarce model performance on this type of mobility. Contrary to our expectations, the radiation model does not perform as well for commutes as for frequent activities.

Our results have broad implication for human mobility, since current mobility models and studies based on aggregated origin-destination matrices may be missing important heterogeneities across groups, with state of the art models performing better on certain classes, ages, and trips purposes.

The dataset we use here contains rich stratification, and uses relatively high spatial resolution. However, for privacy reasons many minor routes, characterized by small number of trips are anonymized and we cannot dive more into their demographic features. We are able to observe flows within districts, but we are unable to decompose them and study them further. For large cities, this still represents flows within the metropolitan area but for smaller towns we can only observe flows to other towns or municipalities, especially in rural areas. Nevertheless, our results indicate that studies of mobility should consider whether or not individuals within an areal unit uses for imputation are heterogeneous—and whether or not this heterogeneity may influence behavior. Further research should consider this question at different spatial scales so that we may understand the scope of this problem.

Data and code availability

The data from Ministry of Transport, Mobility and Urban Agenda of Spain, MITMA ca be found here: https://www.transportes.gob.es/ministerio/proyectos-singulares.

The dashboard can be found here: https://spain-mobility-complexity-72h.streamlit.app/.

The code can be found here: https://github.com/adprabhak/Complexity72h_Mobility.

Acknowledgments

This work is the output of the Complexity72h workshop, held at the Universidad Carlos III de Madrid in Leganés, Spain, 24-28 June 2024. https://www.complexity72h.com

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