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Uncovering the social and spatial effects of fare cuts on public transport with mobile geolocation data

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ABSTRACT

Subsidizing public transit fares is a common policy tool for promoting sustainable mobility and reducing car dependency. Nonetheless, few studies have been able to investigate the causal impact of large fare subsidies on travel behavior patterns. This study investigates the impacts of a nationwide fare reduction policy in Germany: the Deutschlandticket (DT), which priced regional and local transit at 49 euros per month, effective from May 2023 through December 2024. Using large-scale mobile geolocation data from over 11.1 million mobile phone devices, covering 11.7 billion geolocation records in March, April, and May for 2022 and 2023, we employed a time-shifted difference-in-difference model to assess changes in visitor volumes and distance of trips to various locations across Germany. Our results indicate that the D-Ticket increased visit numbers (+26.2%) and increased travel distances (+11.8%) in the first month. Moreover, we found that the impact varied spatially and socioeconomically: urban centers such as high-activity hubs experienced the highest increase in visits and travel distance. Areas visited by a higher share of the foreign population (residents w/o German citizenship) and people from low-rent areas benefited the most, seeing more substantial increases in trips and distances. These results contribute to understanding the effectiveness of transit policy interventions by offering large-scale, high-resolution, and previously unobserved evidence of how they influenced mobility in Germany. Our study provides valuable insights into the broader impacts of public transit pricing, informing equitable and effective fare subsidy policies.

1. Introduction

Reduced public transit fares are widely recognized as an effective measure to improve the accessibility and affordability of urban transportation (UN DESA, 2024; Serebrisky et al., 2009). By lowering fare costs, transit systems can attract more users, encouraging frequent use of public transport and reducing reliance on private vehicles (Pokharel et al., 2023). These changes can not only mitigate traffic congestion and reduce emissions but also support sustainable urban development (Lee and Yeh, 2019; Gohl

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and Schrauth, 2024). Furthermore, reduced transit fares play a crucial role in promoting social equity by making transportation more accessible to economically vulnerable populations, thereby facilitating greater access to essential services, education, and employment opportunities (Guzman and Hessel, 2022).

In May 2023, the German government introduced the Deutschland-Ticket (DT), priced at 49 euros per month, offering extensive access to regional and local public transport. Before, each city or regional transit network had its own pricing, typically ranging anywhere from about 60 to over 100 euros per month (depending on zones, discounts, etc.). The DT's forerunner, the short-term 9-Euro monthly ticket (9ET) was introduced in June, July, and August 2022 (Bissel, 2023) and saw widespread usage, particularly for leisure trips (Liebensteiner et al., 2024; Loder et al., 2024a) and regional travel (Loder et al., 2024b). After the end of the 9ET, in 2023, approximately 20 million people used the DT for at least one month, accounting for around two-thirds of all public transport trips (Krämer and Mietzsch, 2024). The price of the DT was then raised to 58 euros per month starting January 2025 (DB Fernverkehr AG, 2023). The DT has shown promising potential as a transformative measure in promoting public transit use and reducing car dependency.

Measuring the impact of transit fare reductions on individual's behavior is key to understanding their effectiveness and informing future policy decisions. Until now, however, the impact of these transit fare reductions, e.g., the DT, on the mobility behavior of various groups has mainly remained unquantified. This is primarily due to challenges in tracking mobility behavior across large populations at a national scale. Existing studies rely mostly on online surveys and observational statistics, which suffer from limited sample sizes and geographical coverage. Nevertheless, recent studies (Pappalardo et al., 2023; Schlett and Loder, 2024) demonstrate that mobility behavior can be effectively quantified using smartphone data, providing new insights for urban planning and equity analysis (Schlett and Loder, 2024).

In this study, we measure the impact of the D-Ticket intervention on the mobility behavior of 11.1 million individuals living in Germany, leveraging large-scale location data collected from smartphones. Our study focuses on the responses of different socio-economic groups and on different kinds of visited locations (restaurants, shopping areas, etc.). The study offers two key contributions. First, it leverages a comprehensive smartphone dataset to evaluate transit fare policy on a national scale and provides quantitative evidence of how fare reduction influences visitation patterns across different regions. Second, our findings reveal how various regions and population groups are affected by reduced transit fares, highlighting differences based on transit service density, activity type, and population groups.

1.1. Related work

Free or significantly reduced public transit fares aim to promote environmental and social sustainability (Kębłowski, 2020). Policy measures like reduced public transit fares encourage a shift from private cars to public transport, alleviating urban congestion, and reducing emissions (Gohl and Schrauth, 2024). Compared to restrictive measures such as congestion pricing, reducing public transit fares receives greater public support despite its cost, as people favor it for environmental and equity reasons (Lu et al., 2024). One extreme is free public transit (Maciejewska et al., 2023), which is found to significantly increase public transport usage among underprivileged groups in Tallinn, Estonia (Cats et al., 2017). Similar patterns of reduced transit fares have been observed in the United States (Volinski, 2012), France (Kębłowski, 2020), Colombia (Guzman and Hessel, 2022), Brazil (Pereira et al., 2023), and Germany (Rozynek, 2024). Increased ridership driven by reduced public transit fares can foster a more socially equitable transport system by directly supporting less mobile, economically vulnerable individuals (Serebrisky et al., 2009; Waldorf et al., 2025). Yet, as recent work emphasizes, achieving equitable access requires not only affordability but also attention to how transit service and land use jointly shape spatial inequalities in access to opportunities (Janatabadi and Ermagun, 2024).

While fare reductions can boost public transport demand, they may also result in overcrowding and increased pressure on existing infrastructure, as well as impose a financial burden on the government (Andor et al., 2023). Critics argue that fare reduction policies, such as the 9ET and DT, make the underfunding of public transit systems disproportionately benefit higher-income individuals, and fail to generate a meaningful shift away from car usage (Krämer and Mietzsch, 2024). For example, studies have found that transit fare reductions have a limited impact on reducing car usage (VDV and Bahn, 2024b; Ortega and Link, 2025) and often lead to a shift from walking or biking to public transit rather than from car travel (Bull et al., 2021; Vieira et al., 2025). These challenges highlight the need for careful planning and effective capacity management to ensure that the benefits of fare reductions are sustainable.

The DT's forerunner, the 9ET, has been studied with data from traditional surveys, interviews, and regional mobile phone data (e.g., Krämer et al., 2022; Gaus et al., 2023; Loder et al., 2023; Andor et al., 2023). A survey by the Association of German Transport Companies with over 78,000 participants found that 33% of 9ET trips were for leisure and 32% for city travel (Verband Deutscher Verkehrsunternehmen, 2022). During its validity, 38 million unique travelers used the 9ET, with regional trips (>30 km) increasing by 30%–50%, outpacing local public transport growth (Loder et al., 2024b). Additionally, 31% of journeys extended beyond the 9ET users' local networks, and 27% of ticket holders were infrequent public transport users (Verband Deutscher Verkehrsunternehmen, 2022). A separate study on the 9ET showed that 20% of users shifted some car trips to public transport, while regular transit use rose from 29% pre-9ET to 38% during, then dropped to 32% post-expiration (Loder et al., 2024a).

In assessing the policy impact of the DT, traditional surveys and interviews, along with aggregated mobile phone data, continue to provide valuable insights into travel demand responses (Krämer and Mietzsch, 2024). The DT saw a significant increase in PT usage (Follmer and Knie, 2024), particularly for rail travel, weekend trips, and daily commuter rail journeys over 30 km (Telefónica, 2023). Studies show that public transit usage increased by up to 33% (VDV and Bahn, 2024a), with a 9-percentage-point rise in transit trips among DT users (VDV and Bahn, 2024b). However, the policy's effect on reducing car trips remains uncertain, with estimates ranging between 5%–11% of DT trips substituting car travel (VDV and Bahn, 2024b; Helferich et al., 2024; Krämer and Mietzsch, 2024). Considering the combined effects of increased public transit trips and potential reductions in car traffic, the literature remains inconsistent on whether overall mobility has increased due to the DT (Krämer and Mietzsch, 2024). Estimates range from no change (VDV and Bahn, 2024a; Helferich et al., 2024) to a slight (2%–7%) (Follmer and Knie, 2024; Loder et al., 2024b) or a significant rise (VDV and Bahn, 2024a) in travel demand.

These survey-based approaches are constrained by high cost and relatively limited sample size (Lu et al., 2024). Therefore, these surveys have sometimes been combined with mobile geolocation panel data (e.g., Beck et al., 2024; Loder et al., 2024a; Schlett and Loder, 2024; Waldorf et al., 2025; Ortega and Link, 2025). Big geolocation data from mobile phones offers an alternative way that uniquely identifies human mobility at a large scale with high temporal and spatial accuracy (Pappalardo et al., 2023), though it also comes with certain shortcomings. Relevant to the 9ET's impact, Lu et al. (2024) applied crowdsourced data to uncover crowding patterns of transit stations, while (Ortega and Link, 2025) used GPS panel data from 276 individuals, revealing that the fare reduction alone did not trigger a lasting shift from car to transit. Innovative data usage includes mobile phone geolocation data (Beck et al., 2024; Loder et al., 2024a; Liebensteiner et al., 2024; Schlett and Loder, 2024; Waldorf et al., 2025; Ortega and Link, 2025) and crowdsensing data (Lu et al., 2024), providing detailed insights into behavioral changes under the influence of the fare reduction (Harter, 2023; Waldorf et al., 2025). Very few studies on the 9ET have explored its effects on individual mobility patterns and social inclusivity. One qualitative study found that the 9ET substantially improved travel practices and social participation among low-income households with children (Rozynek, 2024). Waldorf et al. (2025) suggested both the 9ET and the DT led to a significant rise in public transport use, particularly among economically disadvantaged groups.

To estimate the causal impact of transport interventions, recent studies have applied quasi-experimental methods (Graham, 2025; Waldorf et al., 2025). For example, Hall and Madsen (2022) estimated the unintended effects of a behavioral road safety campaign by using a quasi-experimental design with fixed effects and instrumental variables. Xiao et al. (2023) applied propensity score matching to evaluate the mobility impacts of shared mobility services. Morton and Ali (2025) evaluated the causal impact of the London Congestion Charge on private car ownership by applying spatial difference-in-differences models in a quasi-natural experiment design. Gohl and Schrauth (2024) estimated the causal effect of the 9ET on air pollution by applying difference-in-differences methods to pollutant data, finding an over 8% reduction in a benchmark air quality index during the subsidy period. Waldorf et al. (2025) applied Propensity Score Matching to estimate the impact of the 9ET and the DT on travel behavior changes, focusing on economically disadvantaged individuals. Despite mostly using small datasets such as survey responses and mobile panel data, these studies offer useful precedents for quasi-experimental evaluation of travel behavior interventions.

There are several research gaps in the literature on public transit fare reductions. First, studies relying on surveys and interviews often face limitations due to small sample sizes, restricting the generalizability of their findings. Second, while much of the current research focuses on individual behavioral responses to fare reductions, there is little understanding of how these policies influence national-scale visitation patterns across different regions by different population groups. This leaves a gap in understanding the spatial dynamics of transit fare interventions and the potentially uneven impacts on subpopulation groups. Third, even in studies that use larger datasets, there is often a lack of quantification of the policy's causal impact, limiting the conclusions about the effectiveness of fare reductions on mobility behavior. Addressing these gaps is essential for comprehensively understanding the broader effects of reduced transit fare policies on urban mobility.

1.2. Outline of this study

This study seeks to quantify the effects of transit fare reductions on visitation patterns at a national scale for different population groups and visiting places, taking the D-Ticket as an example. Using extensive mobile geolocation data from anonymized German adult phone users, we examine how these policy interventions influenced mobility patterns across various regions (hexagons of $\sim 1\ \mathrm{km}^2$) in Germany. Using causal inference, we compare mobility patterns with and without implementing the D-Ticket, focusing on differences in population responses. Specifically, we address the following questions:

- How does reducing public transit fares affect individuals' travel distances and visit frequencies to different regions?
- How do these effects vary across regions with varying levels of public transit supply and activity types?
- How do populations of different incomes and citizenship statuses respond differently to transit fare reductions?

The remainder of this paper is structured as follows. The Methods section (Section 2) describes data sets, mobile phone data processing, regression models, and approaches to analyze heterogeneity in policy effects. The results (Section 3) are presented in three parts: the impact of reduced public transit costs on region-specific mobility patterns, differences across areas with varying levels of transit supply and activity types (clusters based on Point of Interest categories), and the varying effects across different population groups. Finally, the Discussion (Section 4) summarizes the study's results, key contributions, and limitations. To complement the main body of this paper, Appendix A describes additional details of data and processing, while Appendix B and Appendix C present complementary descriptive results. The codes are available at https://github.com/MobiSegInsights/d-ticket-de.

2. Methods

To assess the effects of the D-Ticket on visitation patterns, we utilize extensive mobile geolocation data alongside other data sets that capture key variables that influence visitation behavior, including precipitation, public, regional, and school holidays, and fuel prices. Our study uses mobility data consisting of geolocation records collected from location-enabled smartphone applications

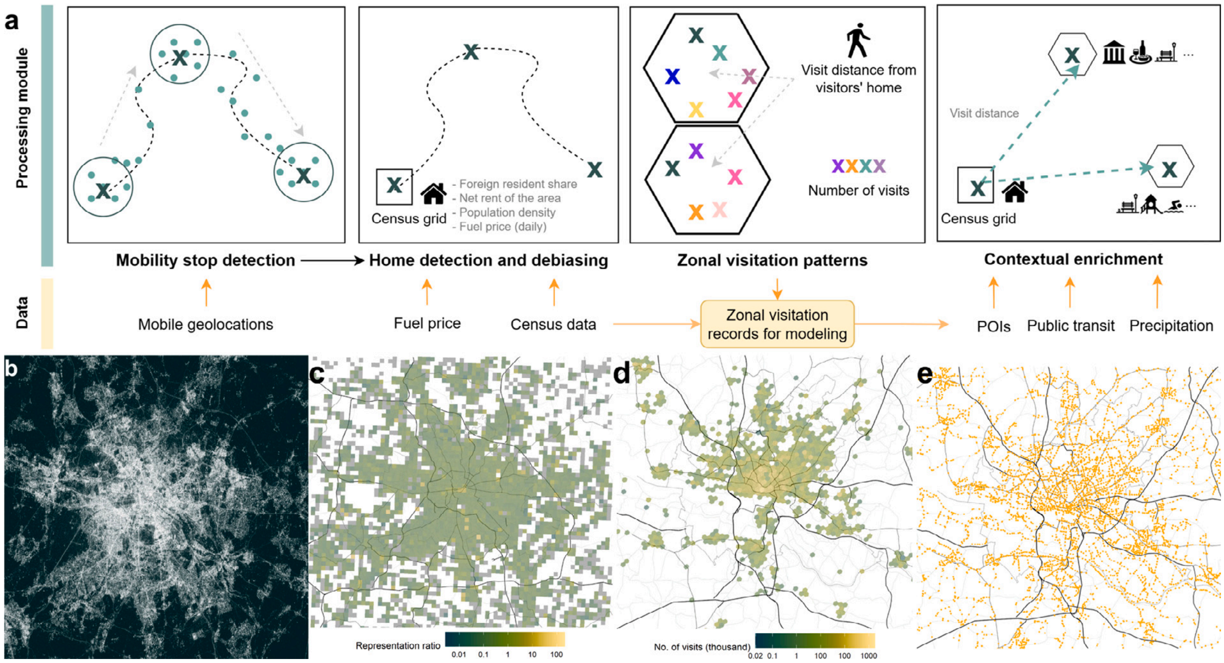

Fig. 1. Data processing workflow for zonal visitation extraction. (a) The process begins with detecting "stops" from mobile geolocation data, identifying locations where users engage in activities (marked with **X**). Home locations are then estimated, and weights are applied to adjust for population biases. The aggregation step compiles place visitation records daily, detailing metrics such as visit distances and number of visits. Each stop is associated with daily precipitation from nearby weather stations, public transit network density, and fuel prices. (b) Raw mobile geolocation data in the Berlin area. The brighter the color, the higher the concentration of these mobile devices' geolocations. (c) Representation ratio in the Berlin area: device count over population size by census grid (1 km). Gray areas are w/o mobile devices but are inhabited by people (see the national version in Fig. A.2). (d) No. of visits in total for the covered hexagons in the Hamburg area. (e) Public transit stations in the Hamburg area. Each point is a station.

from anonymous users. Specifically, the dataset is compiled from various mobile apps used by adult smartphone users in Germany. The raw dataset contains about 11.7 billion geolocations in Germany from 11.1 million devices.

This section outlines the steps to process mobility data (Section 2.1). Section 2.2 presents how we classify the zones based on a few characteristics that may reveal the heterogeneous effects of transit fare reduction. Section 2.3 describes the regression models applied to evaluate the impact of the fare reduction as well as the approach used to analyze heterogeneous responses across regions, activity types, citizenship status, and net rent.

2.1. Processing mobility data

For analyzing the policy effect, we consider two *outcome variables*: the number of visits, and the visiting distance from visitors' homes. Besides the D-Ticket policy, other factors affect the visitation patterns, which we call *contextual characteristics*, including weather conditions, and fuel prices near visitors' residential areas. This section describes how we process mobility data to get *outcome variables* and extract the *contextual characteristics* for zones across Germany.

Fig. 1 illustrates the mobility data processing steps. We first analyze each device's geolocation data to identify stops—locations where users stay for more than 15 min (see Section 2.1.1). Next, we estimate home locations based on temporal visitation patterns (see Section 2.1.2) and correct population bias by assigning individual weights to each device (see Section 2.1.2). Each stop is assigned to a hexagonal zone (Uber Technologies, 2022) at resolution 8 (approx. 0.74 km^2 per cell). We then aggregate visits within each zone, calculating the weighted sum of visit counts and the weighted median of travel distances from home, which serve as *outcome variables* (see Section 2.1.3). Finally, we compile a dataset of visited zones' *contextual characteristics*: stops are further matched with daily precipitation data from nearby weather stations, and perceived fuel prices are estimated by retrieving gasoline prices from nearby stations in each device's home area (see Section 2.1.4).

2.1.1. Mobility data and stop detection

The raw dataset spans the period between March and May for the years 2022 and 2023 (see more details in Appendix A.1 Mobility data.) To extract place visitation patterns, we first detect *stops* from individual geolocation trajectories (*id, lat, lon, time*). A stop is a geolocation/place where an individual device spends at least 15 min at (*id, lat, lon,* $time_{start}$, $time_{end}$), identified using the Infostop algorithm (Aslak and Alessandretti, 2020). Compared to some alternatives, this algorithm is robust against measurement noise, with good scalability to large datasets and the ability to perform multi-user analysis simultaneously (e.g., Hariharan and Toyama, 2004). Details regarding parameter selection and implementation are provided in Appendix A.2 Stop detection.

2.1.2. Home detection and population debiasing

We determine an individual's home area within the census grid cell (1 km × 1 km) where their device spent the most time at night between 22:00 and 07:00 (Zensus 2022, 2024). We filter out devices without reliable home areas, sufficient data, or those belonging to individuals whose inferred home areas are outside Germany. We also ensure that the data for 2022 and 2023 cover the same collection of home areas (see Appendix A.3 Census data). While some individual devices can have records across all the months, others appear in only some due to changes in the underlying mobile app portfolio used for data collection. To ensure sufficient spatial coverage, we retain all devices that meet our selection criteria (see Appendix A.4 Devices filtering), regardless of whether they cover all the months. This approach allows us to maximize the number of covered spatial units in Germany, though it may introduce some noise. To mitigate this, we assign devices to stable home zones, assuming that residents within the same census area share broadly similar mobility patterns.

We address the bias in mobile geolocation data by weighting individual devices based on their home regions. Inverse Probability Weighting (IPW) assigns greater weights to devices from less densely populated areas to counteract the over-representation of urban residents. Weight trimming ensures balance, enhancing the reliability of subsequent analyses (Liao et al., 2025). Using weights (w_p for individual p) reduces population bias, providing a more accurate representation of the population across Germany. The final dataset offers stop records that reflect the mobility of individuals nationwide, facilitating the calculation of locations' visitation patterns from a debiased and general population. Appendix A.5 Population debiasing contains more details of the population weight design.

2.1.3. Zonal visitation patterns

After pinpointing each individual's stop locations, we assign those non-home stops to the corresponding hexagonal zone. We calculate two key quantities that are used as outcome variables of our predictive model: (i) the daily number of individual visits to each zone (hexagon of h3 resolution 8); and (ii) the distance people travel to reach these locations (from their homes) within each zone. We focus on zones with (1) a sufficient number of daily visitors (≥3) and (2) records in the same month for both the treatment year and control year to ensure a robust estimation of the policy impact.

2.1.4. Contextual enrichment

Precipitation and fuel prices affect the visitation patterns of places. Therefore, we extracted daily precipitation (mm) for each hexagon by considering the nearest weather stations (DWD Climate Data Center, 2024; Gohl and Schrauth, 2024), provided that each station is within 80 km of the location and the elevation difference between the location and the station is less than 150 m (Gohl and Schrauth, 2024). We also define each individual device's perceived daily fuel price as the following: historical daily average gasoline prices from all fuel stations within a 10 km radius of each device's home area (Tankerkönig, 2024).

2.2. Classifying zones

This section explains the classification of hexagonal zones based on public transit network density (Section 2.2.1), activity type from POI composition (Section 2.2.2), and visitor and resident demographics (Section 2.2.3). These factors help uncover the heterogeneous effects of transit fare reduction.

2.2.1. Public transit network density

The availability of nearby public transit services significantly influences people's travel behavior and mode choices, whether they opt for public transit or driving, thus affecting visitation patterns across different regions. For each stop location of each individual, we assess the transit network density by calculating the number of public transit stations within an 800-m radius (see Appendix A.7 Public transit data). Based on all the stops in each zone, we calculate the average number of public transit stations nearby.

2.2.2. Activity type

First, we obtain all POIs within the hexagonal zone, categorized using class and subclass designations defined by OSM contributors, with the original dataset comprising thousands of subclasses. To streamline analysis, the data were simplified by grouping these classes into broader, more manageable categories (detailed in Appendix A.6). The study focuses on five kinds of free-time categories — Food and drink, Leisure, Retail, Tourism, and Wellness — used to create activity-type clusters that characterize the built environment in the study area (Liao, 2021). Each zone is represented by a vector containing counts of POIs in these five broad categories. We then proceeded to generate activity-type clusters that categorize regions based on the POI profiles of the zones. To do this, we first applied the Min–Max normalization to the data, which were then clustered using the K-means algorithm, which minimizes the squared error between each cluster's empirical mean and its vectors. To determine the optimal number of clusters (K), values from 2 to 10 were tested, and the silhouette value — a measure of clustering quality — was used to guide selection (Rousseeuw, 1987; Gao et al., 2017). A high silhouette value indicates that samples within clusters are cohesive, and clusters are well-separated. Ultimately, four clusters were chosen based on a combination of the Elbow Method and the Silhouette Score (Bholowalia and Kumar, 2014), as increasing the number of clusters beyond four did not significantly improve the silhouette value.

Table 1
Zonal characteristics considered. The merged group Q2–Q3 corresponds to the middle 50% of zones (i.e., Q2 and Q3 combined). For the activity-type clusters, the percentage of zones in each category is shown in parentheses.

Variable	Notation	Description	Groups[a]
Public transit network density	A_i	Average No. of public transit stations within an 800-m radius of visited places in the zone.	Q1, Q2, Q3, and Q4
Activity-type cluster	C_i	Distribution of no. of POIs in each kind: Food and drink, Leisure, Retail, Tourism, and Wellness.	High-activity hub (0.7%), Balanced mix (3.8%), Recreational area (20.0%), and Low-activity area (75.5%)
Foreigner share	B_i	Average weighted share of foreigner visitors based on their home census statistics.	Q1, Q2–Q3, and Q4
Net rent	R_i	Average weighted net rent of visitors based on their home census statistics.	Q1, Q2–Q3, and Q4

[a] Q_i $(i = 1, 2, 3, 4)$ denotes quantile groups from lowest to highest, each representing 25% of zones.

Table 2
Visitation patterns and co-variates for zone i on day d. The first two variables, representing visitation patterns, are modeled in a log-transformed format. "Policy month" is May. The status of the policy being in effect is true if the year is 2023.

Variable	Notation	Unit	Description
No. of visits	$y_{i,d}^{(\text{visits})}$	–	Estimated number of visitors, i.e., the total sum of visitors' individual weights recorded daily.
Travel distance	$y_{i,d}^{(\text{distance})}$	km	Weighted median distance between the visited zone and the visitors' home locations.
Fuel price	$f_{i,d}$	euro	Daily average price of gasoline across all stations near visitors' home locations.
Precipitation	$p_{i,d}$	mm	Precipitation level at the zone on a specific day.
State	s_i	–	Federal state where the location is situated.
Time effect	$yr(d), m(d), \text{dow}(d)$	–	Temporal indicators including year, month, and day of the week.
Holiday	$\eta_{s,d}$	–	Whether it is a school or regional holiday.
Policy time	DT_d	–	Being in the "policy month", i.e., May.
Policy implementation	post_d	–	Status of the D-Ticket policy being in effect.

2.2.3. Visitors' foreigner share and income level

Each zone is also characterized based on the attributes of its daily visitors, namely the share of foreigners and the average net rent. According to the census statistics, foreigners are defined as residents w/o German citizenship. Net rent is used here as a proxy for income level, given that there is no information available on income at a satisfactory spatial resolution. Net rent is the ratio between the sum of the square meter rent of the apartments and the sum of the rented apartments in residential buildings (excluding dormitories) (Zensus 2022, 2024).

We classify zones into quantile groups within each administrative district ('Kreis' or 'Landkreis', merged by shared name) based on visitor composition, considering both foreigner share and net rent level. Since visitor composition fluctuates daily, we account for these variations when assigning zones to groups. To classify zones based on visitors, we follow these steps:

For each district, we compute the 25% (Q1) and 75% (Q3) quantiles based on the average values of foreigner share and net rent across all available dates. This ensures classification reflects district-level variations rather than absolute values. Using the computed quantiles, we then classify each zone's daily visitor composition into one of nine groups based on its position along the two dimensions (foreigner share and net rent). The classification follows the group labels $Q_i, i = 1, 2-3, 4$, representing different quantile-based categories. A zone is assigned to the group where it falls on most days (i.e., the group with the highest share of days). If more than 30% of its daily records fall within a single group, the zone is classified accordingly. If no single group meets the 30% threshold, the zone is assigned to an "uncertain" category. The 30% threshold is chosen to maximize clustering stability, as determined by the Variance Ratio Criterion (Caliński and Harabasz, 1974). This approach ensures interpretability and consistency across districts and time periods. Compared to clustering algorithms such as k-means, which can be more sophisticated, sensitive to outliers, and require assumptions about distance metrics and data shape, our quantile-based grouping offers greater robustness and adaptability to non-Gaussian, skewed distributions. We opted for this method to retain transparency and simplicity in how zones are grouped while enabling comparisons across space and time.

Table 1 summarizes the zonal characteristics used for classification. Each zone is ultimately assigned to one of four groups, where we analyze potential differences in the effects of transit fare reductions. The spatial distributions of these categorical variables are shown together with the model results in Figs. 5–7 and in Fig. B.2.

2.3. Modeling reduced transit fare effects on visitation

To analyze the effects of reduced transit fares on visitation patterns, we processed extensive national mobile geolocation data, supplemented by various auxiliary datasets. The key variables used in the analysis are summarized in Table 2.

We apply a time-shifted difference-in-difference (DiD) model, also used in previous literature (Hall and Madsen, 2022; Gohl and Schrauth, 2024), to assess the impact of the D-Ticket. In contrast to traditional DiD estimators, these methods utilize two temporal dimensions instead of a single one. The evaluation of the D-Ticket relies on data from March to May 2022 and 2023 (see Fig. 2).

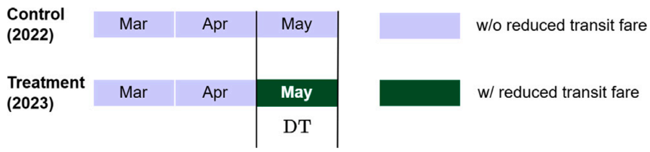

Fig. 2. Time coverage for modeling the impact of the reduced transit fares. The month marked in green is the time the policy is in effect. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The model for evaluating the effect of the DT on zonal visitation is shown in Eq. (1). For simplicity, the zonal index i is omitted on the equation's right side.

$$y_{i,d} = \alpha + \delta \cdot \mathrm{DT}_d \cdot \mathrm{post}_d + \gamma_{s,yr(d)} + \zeta_{s,m(d)} + \mathrm{dow}(d) + \eta_{s,d} + \beta \cdot p_d + \theta_1 \cdot f_d + \theta_2 \cdot f_d \cdot \mathrm{post}_d + \epsilon_{s,d} \tag{1}$$

where $y_{i,d}$ is the dependent variable for zone i at the day d, i.e., $y^{(\text{visits})}_{i,d}$ for travel distance and $y^{(\text{distance})}_{i,d}$ for No. of visits. We regress these outcomes on zone-level fixed effects (α), accounting for all potential time-invariant observable and unobservable characteristics specific to each zone i. DT_d a set of dummy variables indicating whether it is during May, post_d a set of dummy variables indicating the treatment is on, i.e., being in 2023. δ is the coefficient of the effect of the DT. We also include state-year (S-Y FE) fixed effects specific to each federal state ($\gamma_{s,yr(d)}$) to capture any statewide differences across years and state-month (S-M FE) fixed effect specific to each federal state ($\zeta_{s,m(d)}$) to control for variations during the pre- and post-treatment periods within each state. We also control for day-of-week fixed effects, $\mathrm{dow}(d)$, allowing us to only compare visitation patterns on the same day of the week with one another. Finally, we include the state-holiday fixed effect ($\eta_{s,d}$), indicating whether a day d fell on a regional or school holiday in a federal state s_i.

The model includes a series of covariates: precipitation level (p_d) and fuel price of visitors (f_d) were detected at the daily scale, and interactions between fuel price and post-policy ($f_d \cdot \mathrm{post}_d$). They are included because precipitation and fuel prices affect people's travel behavior, especially car users. $\epsilon_{s,d}$ is the error term, clustered at the state level.

The time-shifted DiD model estimates the effect of the DT on zonal visitation by assuming that, in the absence of the policy, visitation patterns between the treatment year 2023 and the control year 2022 would have followed similar trends from Mar to Apr (w/o policy), including May (w/ policy), accounting for observed covariates and fixed effects. Referring to Section 3.1, we observe that a visual inspection of the pre-treatment trends reveals similar trajectories for both treatment and control periods. This visual evidence suggests no major deviations in visitation patterns before the policy change, lending credence to the common trend (parallel trends) assumption (Gohl and Schrauth, 2024). Essentially, the similarity in pre-trends implies that, in the absence of the fare reduction, both periods would likely have followed comparable paths, reinforcing the credibility of the DiD findings.

To validate whether the identified coefficients are significant, we conduct a stratified permutation test with 500 repetitions for each target variable and policy. The permutation test evaluates the robustness of the regression coefficients by randomly shuffling the treatment assignment (post_d) within each state while keeping the data structure intact. By recalculating the coefficients for each permutation, the test generates a null distribution of the coefficients under the assumption of no policy effect. Comparing the actual coefficient to this null distribution allows us to assess whether the observed effect is statistically significant or could occur by random chance.

In addition to the permutation test, we conduct a placebo test by shifting the assumed policy start date to April 1st, using data from March and April 2022–2023. Our results reveal no significant policy coefficient, suggesting that the observed effects are unlikely to be driven by pre-existing trends or other factors unrelated to the actual policy implementation (see Fig. B.1).

2.3.1. Heterogeneity analysis

To identify subpopulations or subregions that may have responded differently to the fare reduction policy, we perform heterogeneity analyses (Hall and Madsen, 2022). These analyses examine the policy's effect on visitation patterns based on activity-type clusters (C_i), public transit network density in these zones (A_i), and visitors' compositions (B_i and R_i). We categorize these zonal characteristics into four quantile groups, i.e., $g_i \in \{q_1, q_2, q_3, q_4\}$, and assign each zone a group for the heterogeneity analysis. In each heterogeneity analysis, the coefficient of interest $\delta\cdot$ is broken down by quantile group, $\sum_{g \in \{q_1, q_2, q_3, q_4\}} \delta_g \cdot$, by which we quantify the heterogeneous policy effect on population groups by income (approximated by residential areas' net rent) and average weighted foreigner share. Additionally, we examine variations across areas characterized by different activity types (POI kinds), transit network density, and urban vs. rural areas. To enhance comparability between cities regarding their visitors, we group visitors based on their net rent and the average foreigners' share of their living zones.

3. Results

In this section, we first describe the observed visitation patterns (Section 3.1). Next, we present the results of the modeling, quantifying the overall policy effects of the D-Ticket (DT) (Section 3.2). Then, we present findings from the heterogeneity analysis, describing how regions with varying levels of public transit density and different activity types responded to the fare reduction (Section 3.3). Finally, we discuss the heterogeneous effects of the policies on different population groups (Section 3.5).

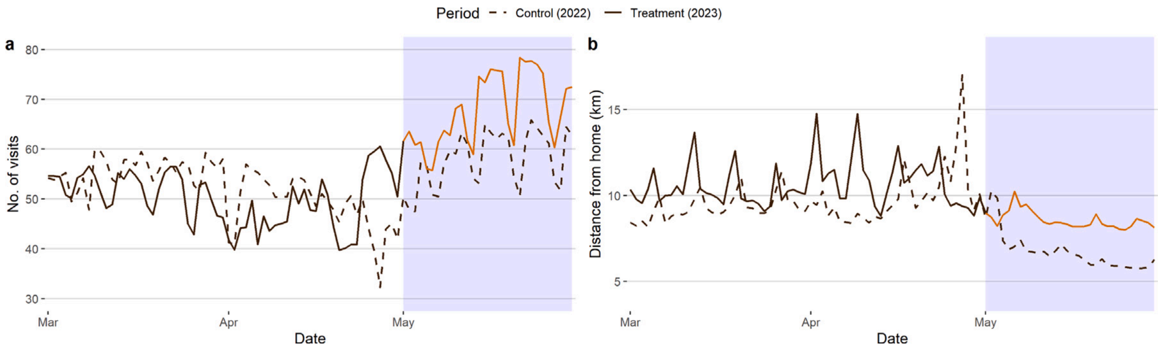

Fig. 3. Visitation patterns across hexagonal zones. (a) Median No. of visits. (b) Median visiting distance from home (km). The lines correspond to median values computed across zones over time for 2022 (dashed) and 2023 (filled). Blue-shaded areas indicate the month of transit fare reduction. The line is displayed in orange during the implementation of the fare reduction policy.

Table 3
Effect of reduced public transit fares on visitation patterns. ***p < 0.01. All results include significant covariates and fixed effects. There are 3,421,661 observations included in the modeling.

	No. of visits (%)	Visiting distance from home (%)
Interaction (δ)	26.18 (0.95)***	11.83 (1.59)***
Adjusted R^2	0.64	0.45

3.1. Visitation patterns overview

After the data processing, the dataset analyzed consists of 4.1 million records across 35,682 unique hexagonal zones. Fig. 3 shows the median value of the number of visits per zone and the median distance traveled to reach these zones. We observe clear weekly patterns, suggesting that the data capture realistic mobility trends. People visit fewer places but travel longer distances during weekends than on weekdays. This weekly variation also highlights the need to control the day of the week.

Visitation patterns between 2022 and 2023 follow similar monthly trends. In May, there was a slight increase in visits and a decrease in travel distances compared to March and April (Fig. 3a). The increase in visits is more pronounced in 2023 when the DT was implemented, while the decrease in travel distance is smaller in the treatment period in 2023 than in the control period in 2022 (Fig. 3b). These findings suggest that the DT had the effect of increasing both visits and the distance traveled.

Outside the transit fare reduction period, the data from the baseline and the policy years exhibit visually similar trends despite some differences. The differences may be attributable to variations in vacation schedules between states and years. This underscores the importance of accounting for other time-dependent variables to better model the policy effect.

3.2. Transit fare reduction impact on visitation patterns

Table 3 shows the effect of the D-Ticket fare reduction on the number of visits and travel distance, computed using the DiD in the model. The transit fare reduction led to approximately a 26.2% increase in the number of visits, and a 11.8% increase in trip distances.

To account for the different timings of the transit fare reduction policy, we also evaluate their effects separately for weekdays and weekends using the same model (see Fig. 4). The policy's effects on both visits and travel distance are greater on weekends than on weekdays. While visits increase by 25.2% on weekdays and 30.1% on weekends, travel distance rises by 10.9% and 14.7%, respectively.

To evaluate the robustness of the estimated policy effect (δ), we conducted a permutation test with 500 iterations. The null distributions of coefficients under the null hypothesis of no policy effect are illustrated in Fig. B.1. The observed coefficients lie outside the extreme tail of the null distributions, with a two-sided permutation p-value < 0.001. This indicates that the likelihood of observing the coefficients in Table 3 under random policy assignment is extremely low. In other words, the estimated policy effects are statistically significant ($p < 0.001$) and robust to randomization inference via permutation testing.

3.3. Effect by public transit network density

The spatial distribution of zones classified based on the density of the public transit network reveals a consistent pattern across Germany's four major cities—Berlin, Hamburg, Munich, and Cologne (Fig. 5a). The most transit-accessible areas are concentrated in the central parts of these cities, extending to the centers of nearby smaller towns. In contrast, the least transit-accessible areas are scattered around the outskirts of these cities but remain within a reachable distance from the urban centers using public transit.

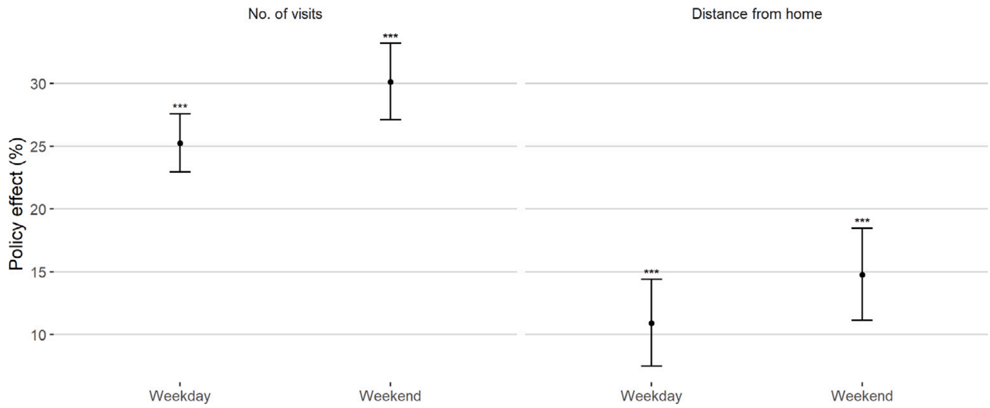

Fig. 4. Effect of transit fare reduction on visitation patterns by weekday/weekend. $^{***}p < 0.01$.

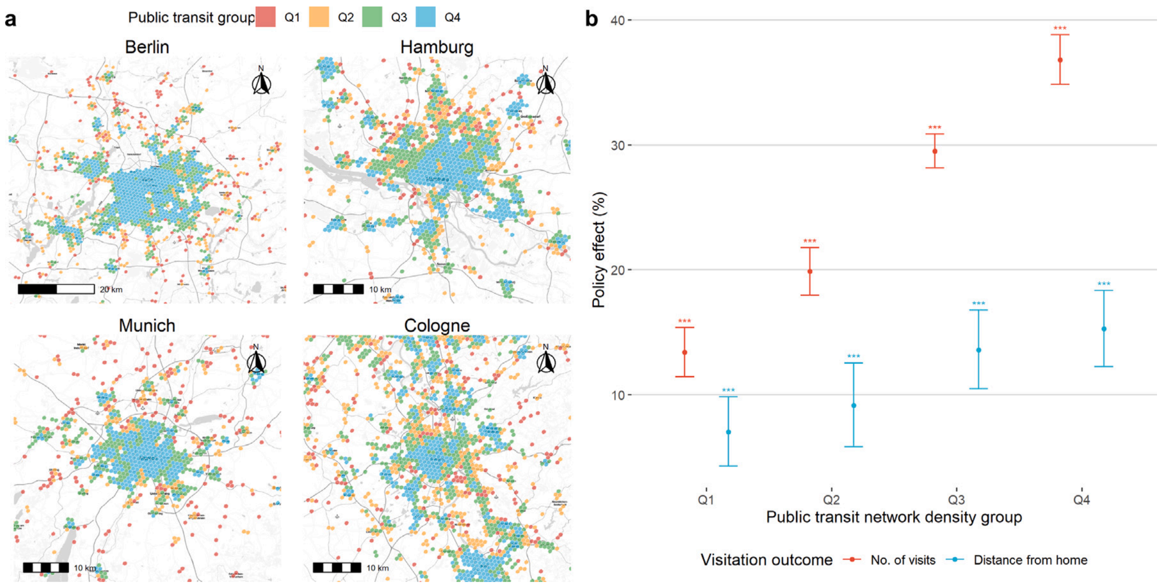

Fig. 5. Effect of transit fare reduction on visitation patterns based on public transit network density at destination. (a) Spatial distribution of public transit density groups across the four major cities in Germany. No. of nearby transit stations: Q1 ≥ 10, Q2 = 10–18, Q3 = 18–28, and Q4 ≥ 28. (b) Interaction coefficients (δ) grouped by levels of public transit network density. $^{***}p < 0.01$.

Fig. 5 shows that the impact of transit fare reduction on visitation patterns varies significantly across areas with different levels of public transit services. Zones with more nearby transit stations experience a stronger policy effect with respect to increased visits, and distance traveled to reach those destinations (Fig. 5b).

3.4. Effect by regional activity characteristics

We categorize study zones into four clusters based on the presence of different kinds of POIs (Food and drink, Leisure, Retail, Tourism, and Wellness). These clusters are meaningful (see Table B.1), as indicated by a silhouette score of 0.54, which reflects moderately well-separated and cohesive groupings according to common interpretive thresholds for clustering quality (Rousseeuw, 1987). Low-activity areas, which are the majority of the zones, are those zones with minimal activity of all kinds, typically representing less dynamic or sparsely active regions. In contrast, high-activity hubs are characterized by high activity values across most kinds, indicating bustling, multi-purpose areas that likely serve as focal points for various activities and services. Recreational areas exhibit low but balanced activity levels, suggesting specialization in leisure or recreational functions with limited diversity.

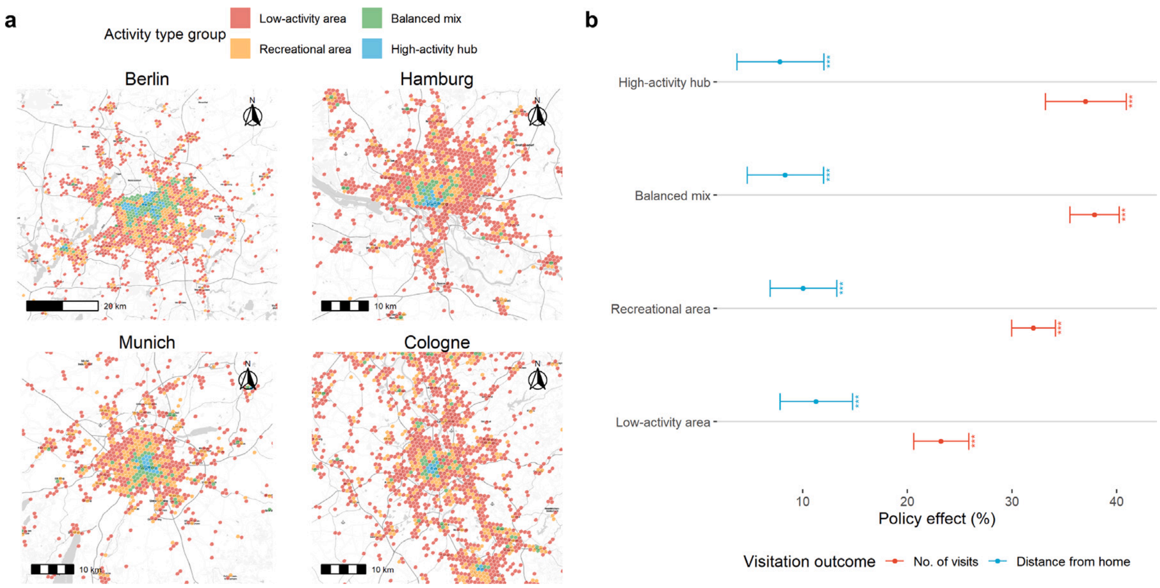

Fig. 6. Effect of transit fare reduction on visitation patterns based on activity-type cluster in destination zones. (a) Spatial distribution of clusters across the four major cities in Germany. (b) Interaction coefficients (δ) grouped by activity-type cluster. ***$p < 0.01$.

Finally, balanced mix zones demonstrate moderate proportions across all kinds of POIs, reflecting areas that accommodate a variety of activities without strong dominance in any particular function. These clusters help capture the built environment's diversity and relationship with the policy's effect on visitation patterns.

The impact of transit fare reduction policies on visitation patterns varies significantly between the four activity-type clusters, both in terms of the number of visits and the distance traveled from home to visit zones in these clusters (Fig. 6). The most substantial policy effect on the number of visits is observed in the high-activity hub cluster. This effect diminishes progressively across the balanced mix, recreational area, and finally, the low-activity area clusters. The strong effect observed in the high-activity hub cluster is concentrated within a very limited number of zones. Instead, the effect of travel distance exhibits the strongest effect in low-activity clusters, followed by recreational, balanced mix, and high-activity hubs. This pattern suggests that the policy may enhance people's ability to travel beyond urban cores and thus increase overall mobility even in lower-density areas, as is corroborated by the substantial increase in regional train ridership (Follmer and Knie, 2024).

3.5. Heterogeneous effects by population groups

To study how the policy impacts different population groups, we classify zones based on the foreigners' share and income level. This classification reveals that there is strong spatial heterogeneity in cities, where people with different backgrounds tend to visit distinct urban areas (Fig. 7).

The policy had a strong impact in areas with a higher foreigners' share suggesting that foreigners without German citizenship are more responsive to transit fare reductions regarding trip frequency (Fig. 7b). For the group of high-foreigner-share (Q4), the lower the income level, the more strongly they responded to the policy, leading to a larger magnitude of increased visits and travel distances than the low-foreigner-share group (Q1). The income-level difference in the policy effect between individuals in the low- and high-foreigner-share groups is minimal compared to regions visited by urban residents (see Appendix C). This is likely due to the higher car ownership among visitors living in non-urban areas, who are less dependent on public transit.

Overall, visitors featuring a higher foreigner share and lower income exhibited the most potent response to the transit fare reduction compared to other groups, particularly those living in urban areas.

4. Discussion

This study presents evidence of the effects of transit fare reduction on visitation patterns in Germany, characterized by the number of visits and the distance from home. The policy effects vary significantly based on regional characteristics and visitor demographics. Part of this evidence includes documenting heterogeneous impacts, with more pronounced effects observed in areas with high public transit access or zones characterized as high-activity hubs. This same evidence highlights the uneven effects of

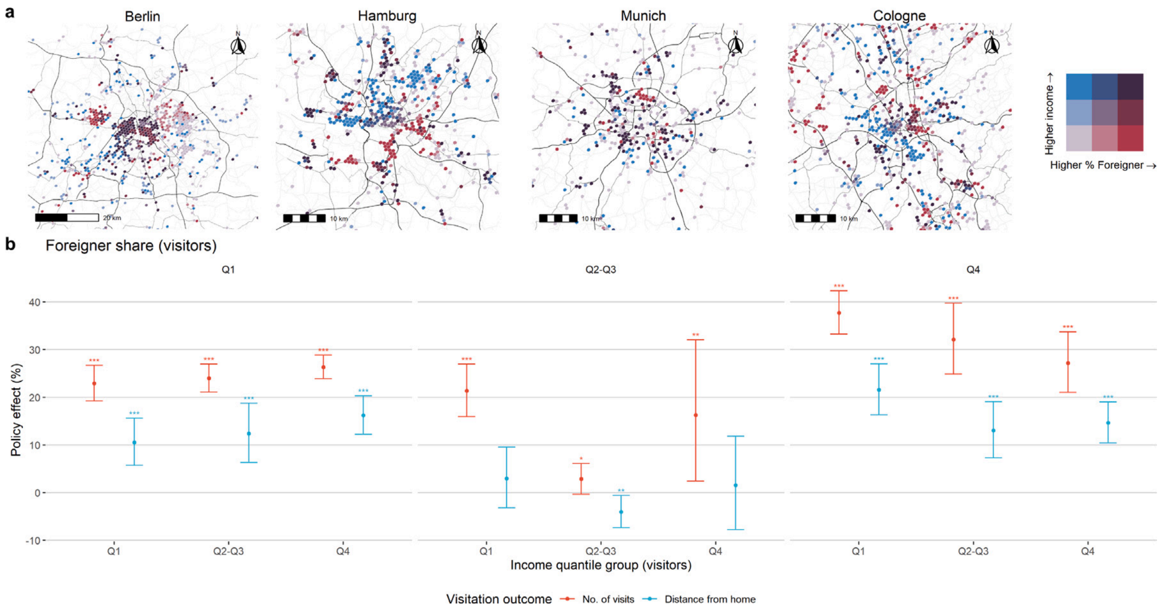

Fig. 7. Effect of transit fare reduction on visitation patterns based on foreigners' share and income levels. Spatial distribution of visitors' groups across the four major cities in Germany: (a) by share of foreigners without German citizenship and net rent level. (b) Interaction coefficients (δ) grouped by foreigners' shares and net rent levels. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

policy outcomes based on socioeconomic factors. Our findings show that the fare subsidy policy had greater impacts in regions visited by populations featuring higher shares of foreigners without German citizenship and lower economic levels. These findings underscore that fare reduction policies can induce substantial changes in travel activity patterns, but more importantly, that their effects vary significantly across regions, socioeconomic groups, and demographic classes, and are further shaped by environmental factors such as transit network density.

The results from the analysis highlight the nuanced impacts of transit fare reduction policies on visitation patterns. First, the DT demonstrated significant increases in the number of visits, with approximately 26.2% growth, and the visiting distance saw an increase of 11.8%. The policy effect was found to be stronger over weekends than weekdays. These findings align with studies reporting a notable rise in PT use, particularly for rail travel, long-distance commuting, and weekend trips (Follmer and Knie, 2024; Telefónica, 2023). Some studies suggest no net increase in total travel volume (VDV and Bahn, 2024a; Helferich et al., 2024), whereas others report a slight (2%–7%) (Follmer and Knie, 2024; Loder et al., 2024b) or significant increase in travel volume (VDV and Bahn, 2024a). Our results suggest a significant increase in travel volume. Possible explanations for these discrepancies include differences in study methodologies, data sources, and regional coverage. Many of the previous analyses rely on survey-based data, which may be subject to recall bias, while our study leverages large-scale mobility data to capture behavioral shifts more precisely.

Despite being carefully de-biased (see Appendix A.5), the underlying population may still not fully capture how the general population reacted to the policy because our data still overly represents foreign residents and Android smartphone users (see Table A.3). The slight over-representation of foreign residents and Android users in our weighted dataset could potentially introduce certain biases in estimating policy effects. Our comparisons suggest that individuals from areas with a higher share of foreign residents showed a somewhat stronger response during the policy month, potentially leading to a slight overestimation of the average effect (see Appendix A.5). Conversely, Android users — who are over-represented in the data — showed slightly weaker responses compared to iOS users, particularly in travel distance, which may lead to an underestimation of the policy's positive impact. While these patterns suggest offsetting biases, the absence of ground truth on mode and user characteristics limits precise quantification. Future work combining mobile data with additional sources is needed to more accurately assess these effects.

Further analysis revealed heterogeneous policy impacts influenced by regional and population-specific attributes. Zones with greater public transit network density exhibited stronger effects in increasing visitation and travel distance. This suggests that the substantial transit fare reduction encouraged more frequent and longer-distance travel patterns. Moreover, the policy effects we observed in lower-density areas suggest subsidizing transit fares can be an important measure to help reduce car dependency even outside urban areas. This observed spatial heterogeneity indicates that coupling fare subsidies with investments in transit infrastructure — especially in areas with lower public transit network density — could amplify positive mobility outcomes.

In terms of activity-type clusters, our findings show that substantial reductions in transit fare costs in Germany have led to an increase in the number of visits and distances traveled to areas that already concentrated a larger number of activities (high-activity hubs). This is a similar dynamic known as the Matthew Effect, commonly observed in the expansion of complex networks (Barabási and Albert, 1999). Areas farther from urban centers (high-activity hubs and balanced-mix clusters) also exhibited a slightly greater increase in travel distance. Socioeconomically, zones frequented by a higher proportion of foreign visitors and low-rent populations experienced stronger visitation effects, while areas primarily visited by native-born populations or high-rent groups showed a less pronounced increase in travel distance. These findings suggest that targeted fare subsidies could promote social equity by improving mobility for economically vulnerable groups.

Despite strong policy effects revealed in the first month, understanding the short-term and long-term effects of public transit fare reductions is essential for evaluating whether such policies produce temporary shifts in behavior or lead to sustained changes in mobility patterns. For example, Tallinn, Estonia, implemented fare-free public transport in 2013. Surveys conducted before and nearly a year after the policy's introduction revealed modest increases in public transport usage. The policy did not significantly reduce car usage, suggesting limited long-term modal shift, but it had lasting institutional and equity-related benefits, making it a valuable example of how fare policy can support broader social policy goals (Cats et al., 2017). Evidence from long-term panel studies suggests that the behavioral response to transit pricing may grow over time. For instance, one study using 13 years of rail ridership data found that long-run fare and service elasticities were nearly twice as large as their short-run counterparts (Voith, 1997).

Although we have found that the effects of the DT were significantly more pronounced in areas with higher public transit network density, a critical limitation of this study is that we lack precise data on the modes of transport used to reach destination zones. As a result, our identified effects should be interpreted as a composite outcome of all travel modes (including driving despite controlling for fuel price) rather than public transit alone. Future work could refine the analysis by inferring mode choices from mobility data — such as through trip speed, duration, and trajectory characteristics — or by combining mobile geolocation data with auxiliary sources like smart card transactions or transport network models to more accurately isolate the role of public transit in observed travel behavior changes. Additionally, May was used as the policy month for the DT analysis because 2022 data includes the 9-Euro-Ticket (9ET) starting from June, making 2022 and 2023 incomparable for evaluating the DT's impact beyond May. This temporal constraint limits the current study to examining only the short-term effects of the DT implementation. Any alternative time frames would require modifications to the current time-shifted difference-in-differences design, making it more difficult to isolate the policy effect from other concurrent factors and contextual changes. Future research should aim to collect additional data spanning longer time periods to assess the persistence and evolution of visitation patterns under the DT policy, as well as to differentiate temporary behavioral shifts from sustained changes in mobility and access. Such longitudinal analysis could also help disentangle seasonal effects, policy fatigue, and structural adaptation among various population groups and travel purposes. Finally, we examine how population-level mobility patterns shifted under the influence of the policy by analyzing spatial visitation patterns. This approach is enabled by the broader population coverage that includes individual devices with records in either time period, provided they share the same home zones. Future research should adopt a more individual-based perspective by leveraging longitudinal trajectories that consistently cover both pre- and post-policy periods, allowing for deeper insights into behavioral changes at the individual level.

5. Conclusion

This study leveraged large-scale mobile geolocation data to evaluate the short-term impacts of Germany's nationwide public transit fare reduction policy — the Deutschlandticket (DT) — on visitation patterns. By analyzing data from over 11.1 million mobile devices and applying a time-shifted difference-in-differences design, we found that the DT increased both the number of visits (26.2%) and average travel distance (11.8%) in its first month of implementation. These behavioral shifts were particularly pronounced over weekends and in areas with high public transit network density. Importantly, our findings highlight substantial heterogeneity in policy impacts. High-activity hubs and areas frequented by foreign-born and lower-income populations experienced the greatest increases in travel, suggesting that fare subsidies can contribute to more inclusive mobility. At the same time, our results indicate that the benefits of such policies are shaped by local transit infrastructure, with stronger effects observed in well-connected zones.

From a policy perspective, these results illustrate the value of large-scale, high-resolution mobility data to examine the effectiveness of transit policy interventions. These findings show how substantial reductions in fare costs, as observed with the DT policy in Germany, can substantially change human mobility patterns. In particular, they show that transit fare subsidies can contribute to making urban and transportation systems more inclusive towards disadvantaged communities, but that the coverage and connectivity of transit networks have a critical role in extending those benefits to larger populations.

Despite the strengths of using large-scale mobile geolocation data (broad population coverage and high spatial resolution), certain limitations must be acknowledged when applying it to transport policy evaluation. Most notably, the data lack modal information, making it difficult to isolate public transit use from other modes of travel. Additionally, despite efforts to adjust for demographic biases, the dataset still overrepresents Android users and foreign residents, which may skew the estimated impacts. These limitations point to the importance of mode inference using the trajectory part of such a data source and integrating mobile data with complementary sources, such as smart card records, travel surveys, or network models, to infer mode choice and better capture socioeconomic dimensions of behavior change. In conclusion, this study demonstrates both the value and necessary caution in using big mobility data, together with robust methods, for timely, scalable, and equality-sensitive transport policy assessment.

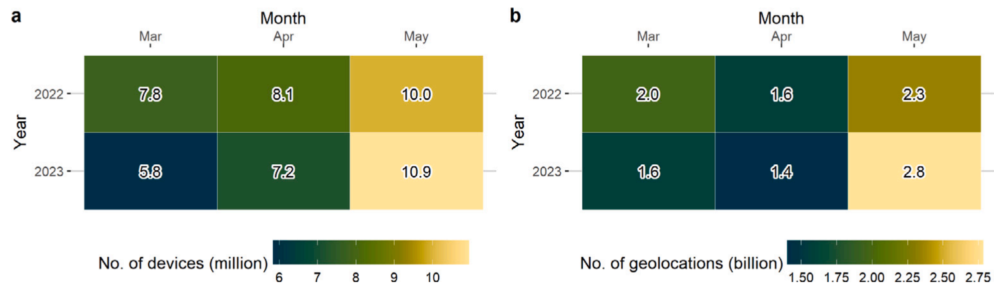

Fig. A.1. Statistics of mobile application data by year and month. (a) Number of unique devices. (b) Number of geolocations.

Table A.1
Parameters configured for using the Infostop algorithm.

Parameter	Definition	Unit	Value
r_1	The maximum roaming distance allowed for two points within the same stop	meter	30
r_2	The typical distance between two stops at the same destination	meter	30
t_{min}	The minimum duration of a stop	min	15
t_{max}	The maximum time difference between two consecutive records to be considered within the same stop	hour	3

CRediT authorship contribution statement

Yuan Liao: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Carl Torbjörnsson:** Writing – review & editing, Investigation. **Jorge Gil:** Writing – review & editing, Validation, Resources, Data curation. **Rafael H.M. Pereira:** Writing – review & editing, Visualization, Validation, Methodology, Investigation. **Sonia Yeh:** Writing – review & editing, Validation, Project administration, Methodology, Investigation. **Niklas Gohl:** Writing – review & editing, Visualization, Methodology. **Philipp Schrauth:** Methodology. **Laura Alessandretti:** Writing – review & editing, Supervision, Project administration, Investigation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to refine the language use. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

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

Appendix A. Data and processing

A.1. Mobility data

The mobile application dataset captures geolocations from various sources, including cell towers, geolocation trackers, and Wi-Fi networks, depending on the source available when specific apps are in use. As a result, the dataset exhibits varying sampling frequencies and spatial resolutions. Additionally, it is subject to sampling bias, as geolocation data is only collected when users actively engage with specific applications on their devices. Fig. A.1 summarizes the number of devices and geolocations covered in the raw data by year and month.

A.2. Stop detection

Infostop algorithm has four configurable parameters to identify stops set as shown in Table A.1. The details of setting up these values can be found in our previous study (Liao et al., 2025).

Table A.2
Descriptive stop statistics. An active day is when at least one stop is detected.

Attribute	min	25%	50%	75%	max
No. of unique hexagons	1	3	6	10	173
No. of active days	1	4	9	17	167
No. of stays	1	5	12	26	1182

Table A.3
Population attributes comparison.

	Foreigner share (%)			Net rent		
Percentile values	25	50	75	25	50	75
Census	0	7.6	20.2	5	6	8
Devices (weighted)	4.1	13	23.8	5	6	8
Devices	7.5	14	23.8	5	6	7

A.3. Census data

The 2022 census in Germany addressed critical questions regarding the country's demographic and housing landscape (Zensus 2022, 2024). The results of the 2022 census provide the current population figures across Germany and detailed information on living spaces. The data on population count is available for various spatial resolutions, from which we applied the 1 km grid in the present study. The population is 82,706,456, with a population density ranging from a minimum of 3 to 24,164 people per km^2 at maximum, and a median density of 64 people per km^2.

We also apply net rent and share of foreign residents with the 100 m grid. Here, foreign residents are defined as residents without German citizenship.

A.4. Devices filtering

The individuals meeting the criteria below are selected for further analysis.

- The identified home location corresponds to a specific grid within the census grids of Germany, indicating that individuals are assumed to reside within the country.
- The identified stops above 12 h are removed.
- One should have at least 15 stops at home.
- The individuals should have more than seven active days, and the number of unique locations should be more than two.

After the stop-detection and filtering process, we have 234.0 million stops from 11.1 million individual devices for further analysis. Their stops have the characteristics shown in Table A.2.

A.5. Population debiasing

After identifying the individuals' homes, we know how many live in each census grid (1 km). The individual devices cover 55% census grids, where 97% of the population resides. The Spearman correlation between the number of devices and the population size has a coefficient of 0.84 ($p < 0.001$), indicating mobile phone data's magnitude-wise representation of the actual population.

Fig. A.2 presents the distribution of individual device counts compared to actual population sizes across census grids (1 km) and municipalities. In Fig. A.2a, a strong correlation is observed between the number of devices and population size within the census grids. Fig. A.2b illustrates the extent to which grid populations are represented in the mobile phone data, with representation rates ranging from 0 to 781. This suggests uneven representation of the population, making careful debiasing necessary.

Inverse Probability Weighting (IPW) is employed to assign each device a weight, calculated as the inverse of the ratio between the number of phone users and the actual population size of the census grid (w_p) (Liao et al., 2025). Some grids exhibit extreme values of this individual weight, particularly where few devices are detected. To manage these extremes, a weight trimming method is applied (Van de Kerckhove et al., 2014), which caps any weight exceeding a threshold (w_0) at w_0. This cut-point weight value is determined by $w_0 = 3.5\sqrt{1 + \mathtt{CV}^2\left(\mathbf{w_p}\right)} \times \mathtt{Med}\left(\mathbf{w_p}\right)$ where CV is the coefficient of variance and Med is the median value. After applying the weighting, the devices in our dataset more accurately represent the general population based on their residential areas (Fig. A.2c).

The population attributes of the census data (100-m grids), devices (weighted), and devices are summarized in Table A.3. The share of covered devices is 87% Android, which is higher than the market share of 68% in April 2023 (Statista, 2025).

The slight over-representation of foreign residents and Android users in our weighted dataset may affect the generalizability of our findings. Based on a randomly selected subset of 1.2 million devices, we compare the weighted average number of visits and travel distances between Android and iOS users, as well as between individuals from areas with high and low shares of foreign residents. As shown in Fig. A.3, the two groups — low and high foreigner share — exhibit similar patterns overall, except in May

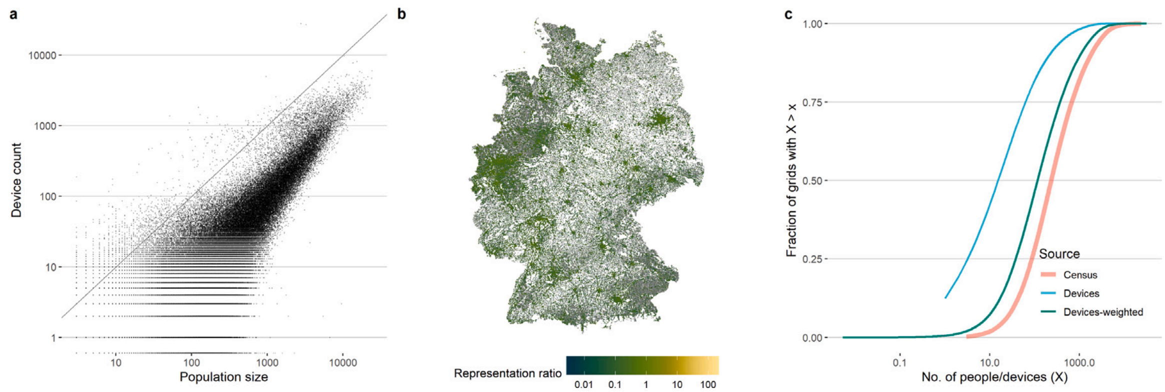

Fig. A.2. Home distribution. (a) Number of devices vs. actual population size by census grid. (b) Representation ratio: device count over population size by census grid (1 km). Gray areas are w/o mobile devices but are inhabited by people. (c) Population size distributions by census grid (the 74% grids covered by the mobile phone dataset): Census, Devices, and Devices after being weighted.

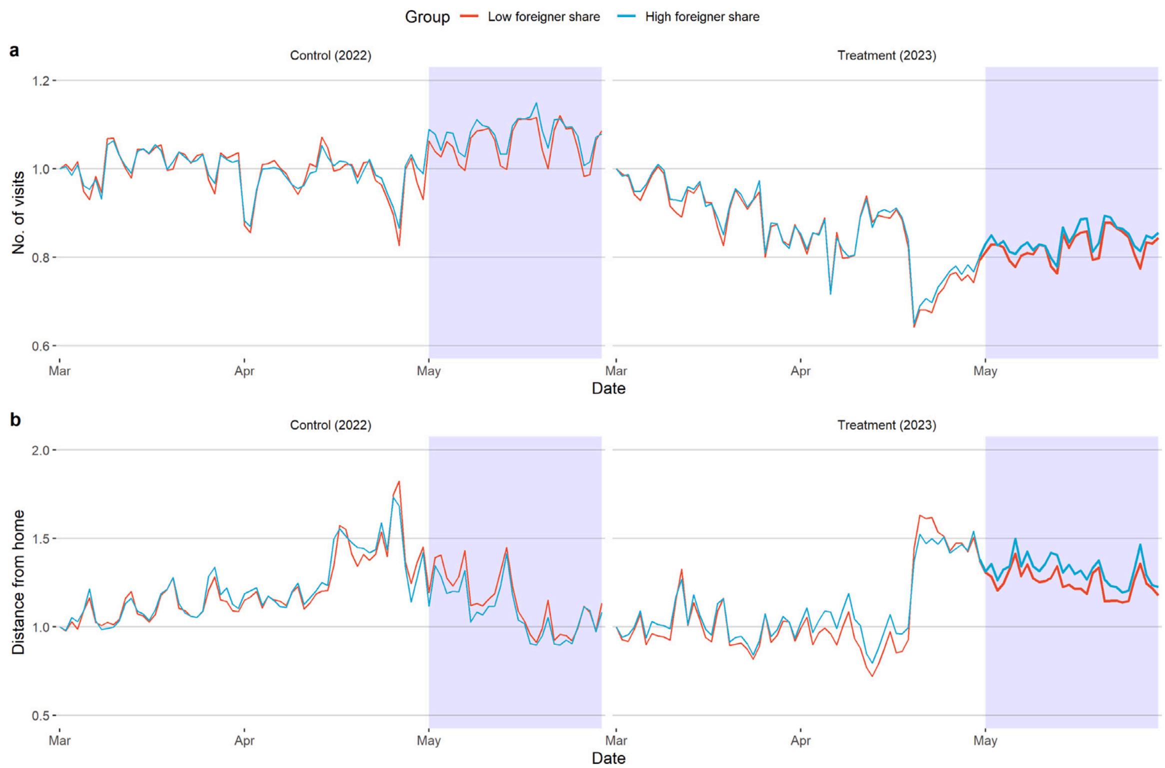

Fig. A.3. Device statistics by share of foreign residents. (a) Weighted average number of visits, normalized to 1 on 03-01. (b) Weighted average travel distance from home, also normalized to 1 on 03-01. Low share = bottom 50% of areas; High share = top 25% of areas, based on the proportion of residents without German citizenship.

2023, when the policy was implemented, suggesting a slightly stronger response among individual devices who live in areas with a higher share of foreign residents, consistent with the heterogeneity analysis (see Section 3.5).

In the control year 2022, Android users showed slightly higher visit counts over time — particularly in May — compared to iOS users (Fig. A.4a). However, this difference largely disappears in the treatment year 2023, suggesting that our Android-heavy sample may lead to a slight underestimation of the policy effect on visit numbers. In contrast, for travel distance, iOS users exhibited greater increases over time than Android users, especially during the policy month in 2023 (Fig. A.4b). This implies that the lower-than-average representation of iOS users in our dataset may result in an underestimation of the policy's positive effect on travel distance.

Fig. A.4. Device statistics by operating system (Android vs. iOS). (a) Weighted average number of visits, normalized to 1 on 03-01. (b) Weighted average travel distance from home, also normalized to 1 on 03-01.

A.6. Point of interest data

Each point of interest (POI) is categorized as a class or subclass, as defined by contributors to OpenStreetMap (OSM). For instance, a specific location might be designated as "class=amenity" and "subclass=shop". The original German POI dataset contains over a thousand distinct subclasses.[1] To streamline the analysis, this study simplifies the dataset by dividing these combinations of class and subclass into broader, more manageable categories that are easier to interpret.

The processing of POI data involved a multi-step technique to ensure accurate categorization and meaningful analysis. Initially, we did class screening to determine which POI classes to include or exclude. Classes such as 'historic', 'tourism', 'leisure', 'sport', 'shop', 'office', and 'craft' were kept. In contrast, others like 'amenity' were selectively filtered to exclude locations not typically associated with stops above 15 min (e.g., recycle points). The 'emergency' class was excluded entirely. Next, we implemented subclass screening for specific POIs by removing irrelevant or stationary entries, such as lamps, boards, and water points. If a subclass was ambiguously labeled as 'yes,' it was standardized to match the class name for consistency. To improve the data's interpretability, broader, cross-kind categories were developed by leveraging GPT-4 API for generating initial classifications, followed by manual processing to refine these groupings. Finally, GPT-4 API was utilized to assign precise place *label* to each class–subclass pair, followed by manual checking to ensure consistency and clarity across the dataset. After processing, we have created 52 place labels.

For the final analysis presented in this study, we focus on places where people are typically involved in free-time activities, involving 23 place labels grouped into 5 kinds (Table A.4).

A.7. Public transit data

The General Transit Feed Specification (GTFS), developed by Google, is an open standard for sharing public transportation schedules. A GTFS static dataset (Google, 2019) comprises multiple text files that collectively provide all necessary details to replicate a transit agency's timetable, including stop locations, route schedules, and vehicle trip timings. We apply the up-to-date GTFS data of Germany from GTFS.DE.[2] The GTFS data are processed to extract the geolocations of all the transit stops.

[1] Retrieved from OpenStreetMap on 2024-04-18: https://download.geofabrik.de.

[2] Retrieved from https://gtfs.de/ on 2024-06-02.

Table A.4
The five kinds of free-time activity types based on the POI labels.

Kind	Included labels
Food and drink	Restaurant, Café
Leisure	Recreational facilities, Art & Culture, Nightclub, Entertainment venues, Parks and gardens
Retail	Retail stores, Community center, Fashion and clothing, Home & Lifestyle, Technology & Hobbies
Tourism	Accommodations, Historic, Information and services, Tourist attractions, Viewing and observation
Wellness	Recreation & Sports centers, Wellness & Relaxation, Training center, Water sports, Wellness and fitness

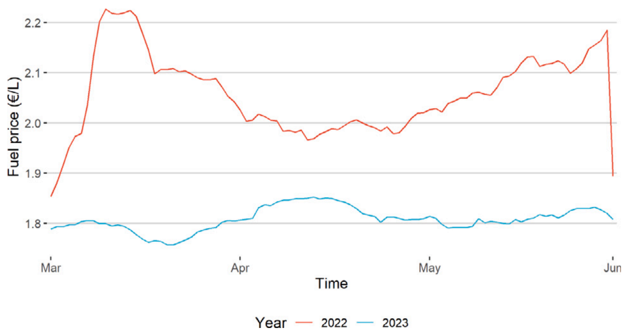

Fig. A.5. Historical fuel price covering the study period.

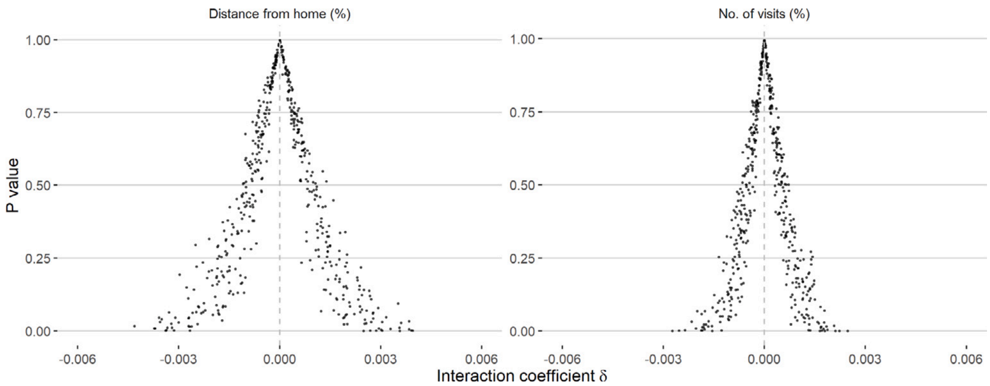

Fig. B.1. Permutation results.

A.8. Fuel price data

Historical fuel price data were sourced from Tankerkönig (2024), provided under a BY-NC-SA-4.0 license, which permits free use for non-commercial purposes. The dataset includes 15,443 fuel stations across Germany, providing geolocations and daily fuel prices for diesel, E90, and E95 gasoline. For the present study, the fuel price is calculated as the average of E90 and E95, as illustrated in Fig. A.5.

Appendix B. Descriptive results

See Figs. B.1–B.2 and Table B.1.

Appendix C. Urban vs. rural residents

For each visitor, we calculate the population density within a 10 km radius around their home location (Duranton and Puga, 2020; Henderson et al., 2021). Visitors are classified as urban residents if this experienced population density exceeds 1000 capita/km^2 (United Nations Statistical Commission, 2020). For visitors classified as urban or non-urban residents, we run the heterogeneity analysis separately exploring the differences between foreigner share and income levels regarding the policy effect. Their results are shown in Figs. C.1–C.2.

In areas frequented by visitors from non-urban regions, we observe a distinct spatial pattern compared to urban visitors across the four cities (Fig. C.1). Non-urban residents tended to visit regions that were more dispersed throughout the cities, extending further into the outskirts.

Table B.1
Four activity-type clusters and their median values across five POI activity kinds for each cluster's zones.

Activity-type cluster	No. of zones	Food and drink	Leisure	Retail	Tourism	Wellness	Public transit access (%)[a]			
							Q1	Q2	Q3	Q4
Low-activity area	26,066	1	1	1	2	0	28.1	27.9	25.6	18.4
Recreational area	6,898	3	3	4	5	4	10.1	19.6	28.3	42.0
Balanced mix	1,311	14	11	20	19	9	2.5	4.8	15.7	77.0
High-activity hub	234	54	34	87	57	10	0.4	0.4	1.7	97.5

[a] The statistics for public transit access group shares are calculated based on the areas analyzed for the DT.

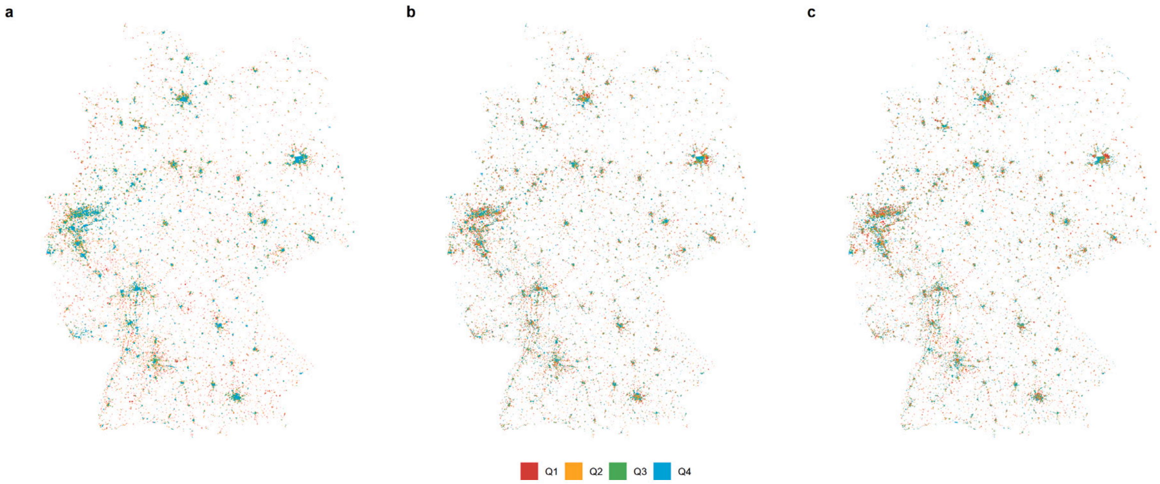

Fig. B.2. Spatial distribution of zone groups in Germany. (a) Public transit access group. (b) Population group of average foreigner share. (c) Population group of residential areas' net rent.

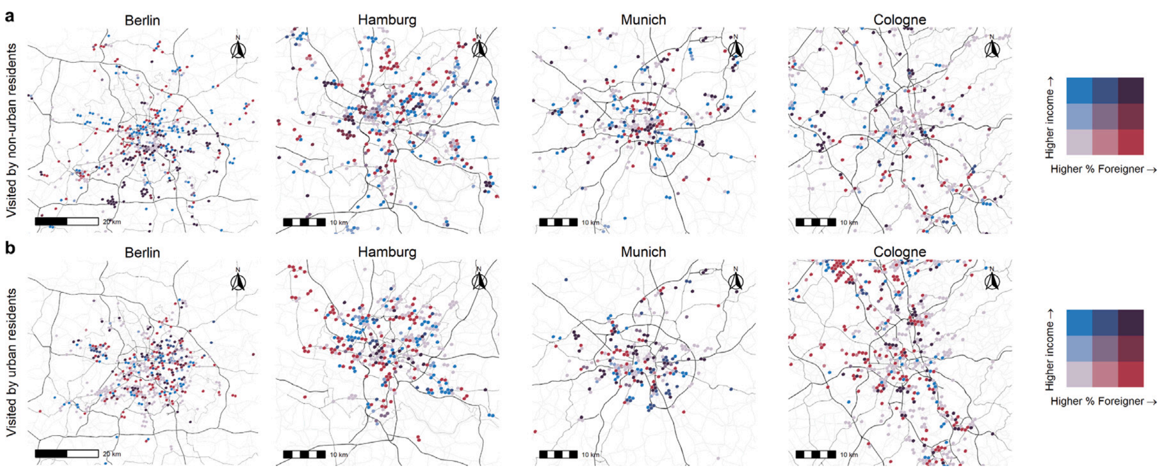

Fig. C.1. Spatial distribution of visitors' groups across the four major cities in Germany: by share of foreigners without German citizenship and net rent level. (a) Non-urban residents. (b) Urban residents.

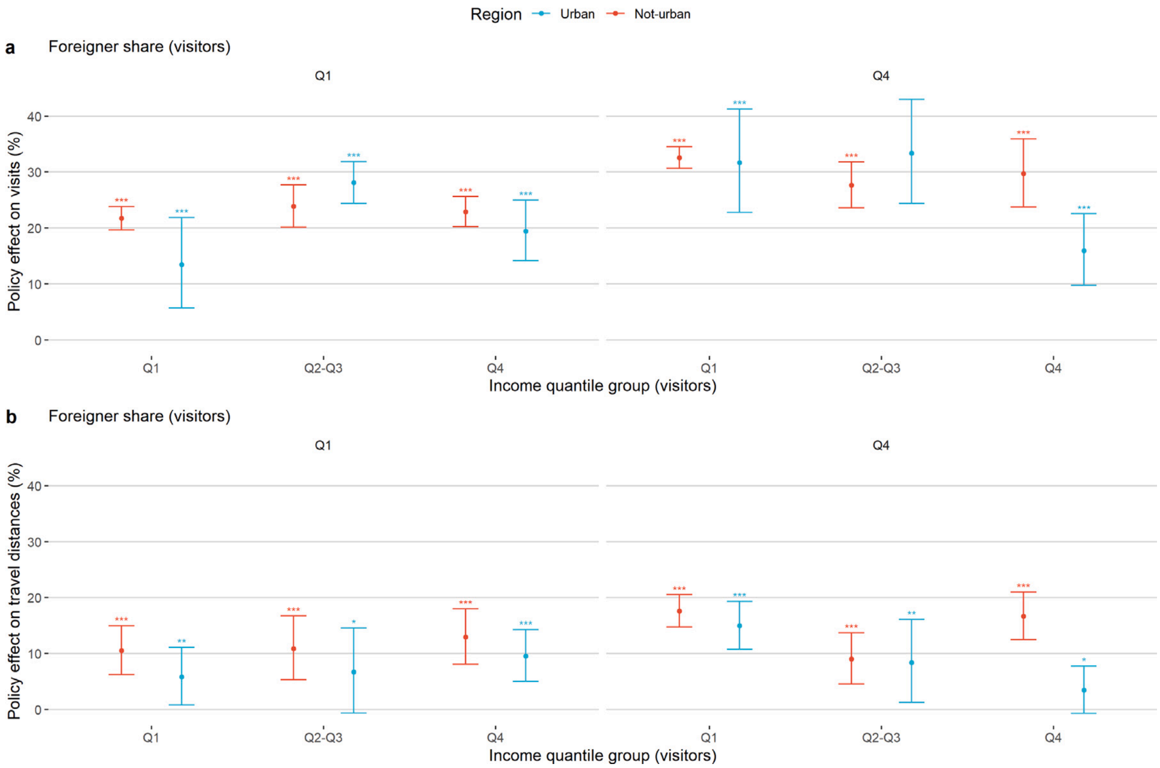

Fig. C.2. Effect of transit fare reduction on visitation patterns: analysis of zones visited by urban vs. non-urban residents based on foreign visitor share and income levels. (a) Policy effect on no. of visits. (b) Policy effect on distance from home. Interaction coefficients (δ) grouped by foreigner shares and net rent levels. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Data availability

The authors do not have permission to share data.

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