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Measuring the Attractiveness of Trip Destinations: A Study of the Kansai Region of Japan

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Measuring the attractiveness of trip destinations: A study of the Kansai region of Japan

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Abstract

This study proposes a novel concept of a regional attractiveness index based on human mobility flows. Assuming that individuals' mobility choice is based on utility maximization, this study aims to recover the attractiveness of trip destinations by estimating the gravity equation for interregional trip flows. Using mobility data from a Person Trip Survey and mobile phone data in the Kansai region of Japan, this study investigates whether different trip purposes (e.g., commuting to office and school, recreational trips, business trips, and returning home) and seasonal and tourism factors (e.g., holidays, events, and amusement facilities) can reveal spatial and temporal variations in the attractiveness of trip destinations. This study found that the proposed approach using interregional trip flows can effectively capture the extent to which trip destinations attract people from a region-wide perspective. As real-time human mobility data become increasingly available, the new index of regional attractiveness is expected to become a key performance indicator for daily monitoring of urban and regional economies.

JEL classification: J61, R23, R41

Keywords: Regional attractiveness index, Person trip survey, Human mobility, Gravity equation, Exploratory spatial data analysis

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1. Introduction

Economic activities in both urban and rural areas are sustained by not only the internal mobility of local residents but also the daily inflow of people for various purposes, including commuting to work or school, business trips, shopping, and sightseeing. However, the coronavirus disease 2019 (COVID-19) pandemic has affected conventional lifestyles since 2020, leading to a decline in business and tourism demand and a transition from daily commuting to remote work. How this decreasing demand for interregional trips affects local economic performance poses a challenge for local governments and policymakers.

One of the crucial policy strategies in response to the pandemic was to monitor the key performance indicators of the local economic situation daily. However, local economic performance indicators are generally unavailable as high-frequency data because research based on large sample surveys takes a long time to yield meaningful results. Therefore, this study explores the potential of big data to advance the conventional style of policymaking and evaluation (Einav and Levin, 2014; Varian, 2014; Li et al., 2018).

This study aims to conduct policy-oriented research on urban and regional issues to bridge the gap between academic research and policymaking. The demand for social implementation in academic research is increasing as policymakers require research outcomes to address social challenges, but few relevant studies are available. Nevertheless, with the increasing availability of high-frequency big data, policymaking and implementation must be faster than ever. Therefore, drawing on Ballou and Pipkin (1977) and Baxter (1979), we propose a novel regional attractiveness index based on human mobility data grounded in the concept of the attractiveness of trip destinations. Assuming that trip choice is based on utility maximization, the purpose is to recover the attractiveness of trip destinations by estimating the gravity equation of interregional trip flows. In addition, the estimated regional attractiveness index is visualized on a map as an exploratory spatial data analysis (ESDA) to gain deep insights into its spatial structure.

The proposed novel approach solves the complexity of human mobility big data by reducing it to a single scalar index. This complexity comes from two-dimensional network data, which makes it challenging for policymakers to draw straightforward implications from the raw origin-destination (OD) flow data. Generally, centrality measures are standard in network science, and some studies extend them along with the increasing availability of real-time mobility data (Chi et al, 2016; Nanni et al., 2020; Xu et al., 2023). Aoki et al. (2023) propose a new approach to identifying city centers, introducing the scalar potential field of human flows. This research also emphasizes the importance of rich behavioral data on OD flows and recovers the subjective attractiveness of the trip destination, focusing on the distance decay parameter of the gravity equation.

The present study advances the human mobility literature by reconsidering the conventional spatial interaction models. Gonzalez-Feliu and Peris-Pla (2017) propose an attractiveness indicator of retail activities based on the gravity equation of trip flows. Although they specify the market potential form under the constant distance decay parameter assumption, we consider the heterogeneous parameters across the regions. Following the idea of the competing destinations model by Fotheringham (1981, 1983), Ito (1986), Yano et al. (2000, 2003) and Babb (2021) estimate heterogeneous distance decay parameters across the origin regions in the conventional gravity equation. Although regional attractiveness is measured by the population size parameter to examine whether larger cities offer opportunities for working and living, Ito (1986), Yano et al. (2000, 2003) and Babb (2021) found that the distance decay parameters estimated in the origin-specific gravity equation vary across origin locations, suggesting that some origin regions increase outmigration costs. In contrast, this study considers heterogeneous distance decay parameters in the destination-specific gravity equation based on Haynes and Fotheringham (1985). Drezner and Zerom (2024) observed that more attractive facilities attract customers from long distances, suggesting that the facility attractiveness decreases the distance decay parameter. Therefore, this study attempts to capture the perceived attractiveness of trip destinations from the distance decay parameter.

Further, we contribute to the tourism literature by proposing a new way to measure the regional attractiveness of trip destinations. Cracolici and Nijkamp (2009) point out that the dynamic nature of tourist attractiveness should be considered, implying that the attractiveness of trip destinations depends on the trip purposes. Furthermore, Salinas Fernández et al. (2020) emphasize the need to monitor the competitiveness of tourist destinations. Because the tourism industry experienced severe economic deterioration during the pandemic, the monitoring index proposed in this study has important implications for the industry. Wu et al. (2023) investigated the attractiveness of Meeting, Incentive tour, Convention, and Event (MICE) cities in China using spatial network analysis, and the proposed approach in this study provides additional insights into their findings.

This study reveals spatial and temporal heterogeneity in the attractiveness of trip destinations. First, it considers how the attractiveness of trip destinations changes for different trip purposes (e.g., commuting to the office and school, recreational trips, business trips, and returning home). For this purpose, this study relies on the Person Trip Survey of the Kinki Metropolitan Area (Keihanshin Metropolitan Area Transportation Planning Council, 2023), which provides comprehensive information on various aspects of daily mobility in terms of "why," "from where to where," "who," "when," "how," and "for what purpose." Second, this study relies on real-time big data on human mobility based on mobile phone data to focus on the seasonal and tourism factors of trip flows. Based on the high-frequency data, this analysis can reveal how the attractiveness of trip destinations fluctuates seasonally throughout the year.

The findings show that the proposed approach using interregional trip flows captures the extent to which trip destinations attract people from a region-wide perspective. Although the regional attractiveness index is likely to be high in core urban areas, some rural regions have high values for different purposes of trips and seasonal factors. This is consistent with Zhong et al. (2015), who found variability in the mobility patterns. As big data on human mobility based on smartphones become ubiquitous, our proposed approach can be applied to the data to secure valuable insights for local economic revitalization and inform policymaking.

This paper proceeds as follows. Section 2 introduces the concept of the regional attractiveness index based on the gravity equation of interregional trip flows. Section 3 describes two different datasets of the interregional trip flow data in the Kansai region of Japan. Section 4 provides the estimation results for the regional attractiveness index and explores the spatial characteristics. Section 5 concludes the paper.

2. Method

2.1. Attractiveness of Trip Destination

This study revisits the conceptual idea of “attractiveness of trip destinations” discussed by Ballou and Pipkin (1977) and Baxter (1979) and develops a simple trip choice model to measure the attractiveness of trip destinations based on recent theoretical models (Ahlfeldt et al. 2015; Redding and Rossi-Hansberg 2017; Su, 2022; Miyauchi et al., 2022). The standard discrete choice model of interregional mobility predicts that individuals travel to a region where they can obtain the highest utility among the choices. In the literature, Nakajima and Tabuchi (2011) argue that population movements are motivated by the utility gap between regions.

Following Baxter (1979), the attractiveness of trip destinations is assumed to be related to trip distance, which is also empirically supported by Drezner and Zerom (2024). For example, a recreational trip to a destination may be an activity that increases individual utility, even if it is a long-distance trip. However, daily commuting decreases individual utility as a mobility cost. Importantly, trip distance affects the perceived attractiveness of trip destinations, varying in terms of the destination and purpose.

The attractiveness of trip destination can be interpreted as the individuals’ utility obtained from the amenity consumption discounted by the trip costs from locations i to j. This study introduces the discount factors of objective and subjective trip costs, $f_O(D_{ij})$ and $f_{S,m}(D_{ij})$, respectively, where D_{ij} is the bilateral distance between locations i and j. The range of the objective and subjective discount factors is from zero to one. The objective trip costs are common among trips, whereas the subjective trip costs vary between trips in terms of trip purposes. When $f_{S,m}(D_{ij}) = 1$, this is a standard assumption of the trip choice model.

This study considers that the attractiveness of the trip destination is reflected in the parameter of the subjective trip costs. The attractiveness of trip destinations must be high as the discount factor of subjective trip costs approaches to one because it means individuals obtain higher utility from the trip. Based on this assumption, this study proposes an empirical approach to estimating the index of regional attractiveness based on interregional trip flows.

2.2. Micro-foundation of Trip Choice

The trip choice model is considered a discrete choice model based on the random utility model (Ahlfeldt et al. 2015; Redding and Rossi-Hansberg 2017; Monte et al. 2018; Su, 2022, Miyauchi et al., 2022).[1] Suppose that there are N locations in the economy. Each individual who resides in the location i decides to travel to location j for the purpose m. Individuals choose one of N trip locations to maximize their utility. The total utility of each individual, $\tilde{V}_{ijm}$, is defined as follows:

$$\tilde{V}_{ijm} = V_{ijm} b_{ijm}, \tag{1}$$

where V_{ijm} is the deterministic utility and $b_{ijm} > 1$ is a stochastic utility including amenities related to locations i and j. The deterministic utility V_{ijm} is defined as the indirect utility obtained from the utility maximization, as defined below.

The preferences of individuals are defined over the amenity consumption in trip destination j (A_j), the consumption of non-trip goods and services in residential location i (C_i), and the discount factors of objective and subjective trip costs from locations i to j, $f_O(D_{ij})$ and $f_{S,m}(D_{ij})$. The utility function is assumed to take a Cobb-Douglass form as follows:

$$U_{ijm}(A_{jm}, C_i) = \frac{1}{\mu^{\mu}(1-\mu)^{1-\mu}} \left[f_O(D_{ij}) f_{S,m}(D_{ij}) \right] A_j^{\mu} C_i^{1-\mu}, \tag{2}$$

where μ is the expenditure share for amenity and the second term on the right-hand side. The budget constraint is expressed as follows:

$$P_{A,j} A_j + P_{C,i} C_i = I_i, \tag{3}$$

where $P_{A,j}$ is the price of amenity in trip destination j, $P_{C,i}$ is the price of good in residential location i,

[1] Crozet (2004) and Kondo and Okubo (2015) consider a theoretical framework in which stochastic amenities are introduced additively, called additive random utility models. Furthermore, Ahlfeldt et al. (2015), Redding and Rossi-Hansberg (2017), Monte et al. (2018), and Kondo (2020) rely on a random utility model based on type II extreme value distribution (Fréchet distribution).

and I_i is the individual's income in location i.

Utility maximization yields the demand functions for amenities in location j and non-trip goods and services in location i, and substituting them into the utility function in Equation (2), we have the indirect utility function as follows:

$$V_{ijm} = \frac{I_i}{P_{A,j}^{\mu} P_{C,i}^{1-\mu}} \left[f_O(D_{ij}) f_{S,m}(D_{ij}) \right]. \tag{4}$$

Next, a stochastic utility component is assumed to be drawn from an independent Fréchet distribution. The cumulative distribution function of Fréchet distribution, $F_{ijm}(b)$, is expressed as follows:

$$F_{ijm}(b) = \exp\left(-B_{im} B_{jm} b^{-\alpha}\right), \qquad B_{im} > 0, \qquad B_{jm} > 0, \qquad \alpha > 1, \tag{5}$$

where B_{im} is a scale parameter that determines average utility derived from the residential location, B_{jm} is the scale parameter that determines the average utility derived from trip destination j, and α is a shape parameter (Ahlfeldt et al., 2015; Redding and Rossi-Hansberg, 2017).

An individual chooses a choice that maximizes utility among all choices for the trip purpose m. The assumption of Fréchet distribution yields the probability of trip for the purpose m from location i to location j as follows:

$$\pi_{ijm} = \frac{B_{jm} P_{A,j}^{-\mu\alpha} \left[f_O(D_{ij}) f_{S,m}(D_{ij}) \right]^{\alpha}}{\sum_{k=1}^{N} B_{km} P_{A,k}^{-\mu\alpha} \left[f_O(D_{ik}) f_{S,m}(D_{ik}) \right]^{\alpha}}, \tag{6}$$

where the variables in location i are offset. This is the standard logit form obtained from the discrete choice model.

The objective and subjective trip cost functions from locations i to j are formulated as a monotonic function of trip distance as follows:[2]

$$f_O(D_{ij}) = D_{ij}^{\delta} \text{ and } f_{S,m}(D_{ij}) = D_{ij}^{\beta_{jm}}, \tag{7}$$

where $\delta \leq 0$ and $\beta_{jm} \leq 0$ are the distance decay parameters for objective and subjective trip costs, respectively. Note that the internal trip costs $f_O(D_{ii})$ and $f_S(D_{ii})$ are assumed to be one. When $\beta_{jm} = 0$ and $f_{S,m}(D_{ij}) = 1$, this is a standard homogeneous assumption in distance decay parameter in the literature of migration and commuting choice.

By inserting Equations (7) into Equation (6), the trip probability from locations i to j for the purpose

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[2] Martínez and Veigas (2013) examine several functional forms of distance decay function. Halás et al. (2014) further discuss distance decay functions for daily travel-to-work.

m can be expressed as follows:

$$\pi_{ijm} = \frac{B_{jm} P_{A,j}^{-\mu\alpha} D_{ij}^{\alpha(\delta+\beta_{jm})}}{\sum_{k=1}^{N} B_{km} P_{A,k}^{-\mu\alpha} D_{ik}^{\alpha(\delta+\beta_{jm})}}. \tag{8}$$

Note that the distance decay parameter consists of three parameters: the perceived attractiveness of the trip destination (β_{jm}), the trip costs proportional to trip distance (δ), and the shape parameter (α). The heterogeneity of the distance decay parameter originates only from the parameter β_{jm}.

Equation (8) captures the individual decision-making process for the trip choice. The trip probability from locations i to j is likely to be high in location j with lower amenity price. The trip probability from locations i to j decreases as the trip distance increases. The trip probability is higher in the trip destinations with higher attractiveness that lowers subjective distance decay parameter β_{jm}. This study aims to recover spatial and temporal variations in the subjective preference included in Equation (8).

Although the trip probability of each individual cannot be directly observed, the realized trip flows are observable. This study estimates the distance decay parameter by fitting the mobility data to the model. The expected number of trip flows $T_{ijm} \geq 0$ is expressed as $\pi_{ijm} L_i$, where L_i is the total population in location i. Taking logarithms on both sides, the gravity equation for trip flows can be expressed as follows:

$$T_{ijm} = \exp\left(\phi_{jm} \log D_{ij} + \kappa_{jm} + \psi_{im}\right), \tag{9}$$

where

$$\begin{aligned} \phi_{jm} &= \alpha\left(\delta + \beta_{jm}\right), \\ \kappa_{jm} &= -\mu\alpha \log P_{A,j} + B_{jm}, \\ \psi_{im} &= \log L_i - \log\left(\sum_{k=1}^{N} B_{km} P_{A,j}^{-\mu\alpha} D_{ik}^{\alpha(\delta+\beta_{km})}\right). \end{aligned} \tag{10}$$

The regional attractiveness index proposed by this study is estimated as $\phi_{jm} \leq 0$, which captures the extent to which trip destination locations attract people from other locations. The regional attractiveness index is expected to have negative values, and locations with values close to zero are more attractive, suggesting that these locations attract people from more distant locations with less trip costs.

The critical point in the gravity equation of trip flows is that the regional attractiveness index can be estimated from the observed interregional trip flows even though the trip preference of each individual is unobservable. However, the perceived attractiveness of the trip destination β_{jm}, the distance decay parameter δ, and the shape parameter α cannot be distinguished separately and are estimated as a single parameter ϕ_{jm}.

Silva and Tenreyro (2006) suggested a method for estimating the gravity equation.[3] Therefore, this study employs their approach of the Poisson regression to consider zero-flow issues. The destination-fixed Poisson regression model is as follows:

$$\Pr(T_{ij} = t_{ij}) = \frac{\exp\left(-\lambda_{ij}(\boldsymbol{\theta}_{jm})\right)\left(\lambda_{ij}(\boldsymbol{\theta}_{jm})\right)^{t_{ij}}}{t_{ij}!}, \qquad t_{ij} = 0, 1, 2, \dots,$$
$$\lambda_{ij}(\boldsymbol{\theta}) \equiv \exp(\phi_{jm} \log D_{ij} + \kappa_{jm}), \tag{11}$$

where t_{ij} is the number of trip flows, and $\boldsymbol{\theta}_{jm} = (\phi_{jm}, \kappa_{jm})$ is the parameter vector, including the constant term κ_{jm} and the parameter of the regional attractive index ϕ_{jm}. This Poisson regression is estimated by fixing the destination location, which leads to a heterogeneous distance decay parameter for the destination location j. Therefore, the fixed effect ψ_i in Equation (9) is omitted in Model (11). We do not further include control variables, such as population, in the origin location i in Equation (11) to capture the aggregate attractiveness of trip destinations by the coefficient parameter ϕ_{jm}.[4]

3. Data

3.1. Person Trip Survey

The first dataset of the interregional trip flows is the 2010 Person Trip Survey conducted in the Kansai region (Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama prefectures). Figure 1 shows the survey area in the Kansai region. The survey captures daily human mobility based on factors such as the purpose of the trip, origin and destination, individuals involved, time and mode of transportation, and the trip's intent. Such detailed information on human mobility is essential for gauging the attractiveness of trip destinations, as regional attractiveness is not invariant but depends on the trip purpose.

Person Trip Surveys are generally conducted every ten years in each urban area across Japan. The first survey in the Kansai region was carried out in 1970, and the fifth was conducted in 2010. Publicly available data are aggregated at the survey unit level, which is more disaggregated than the municipal unit level. There

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[3] See also Ramos (2016), who summarized previous studies on the gravity equation in migration.

[4] Another specification is to introduce the cross-term of amenity variables and trip distance. The coefficient parameter of trip distance can consider each effect of the amenity variables in the regional attractiveness index. However, this approach must prespecify amenity variables. We prefer to a two-step approach to explore what factors increase the attractiveness of trip destination after estimating the Poisson regression model in Equation (11).

are 432 survey areas in the 2010 Person Trip Survey. This study ran 3,024 ($= 432 \times 7$) regressions of the gravity equation for each destination location j for each trip purpose m using the Person Trip Survey. If the number of observations (i.e., the number of positive trip flows) is less than 10, the distance decay parameter was not estimated owing to the small sample bias.

This study further imposes a condition of internal trip distance to avoid the bias arising from neighboring outliers. Some municipalities have small areas, while others have large areas, suggesting that cross-border trips are relatively easy for small ones. Individuals who reside near the border are also likely to affect the number of cross-border trips. To control for neighboring municipalities with outliers, this study considers the diameter of the municipal area as an intra-municipal distance. If inter-municipal trip flows do not exceed the diameter of the municipal area, they are regarded as internal trip flows and omitted from the sample. The diameter of each municipality (km) is calculated as $2\sqrt{\mathrm{Area}_j/\pi}$, where Area_j is the area of municipality j and π is the circular ratio.

Table 1 presents the descriptive statistics on trip flows and bilateral distances between the survey areas. This study considers seven types of trips for different purposes (total, commuting to office, commuting to school, free, business, returning home, and unknown).[5] Note that the descriptive statistics include many zero trip flows. For example, the median of trip flows takes a zero value, meaning that most trip flows are concentrated between a small part of the survey areas. The travel distance was measured as the great circle distance from the longitude and latitude of the reference point of the survey area.[6] The reference points for measuring the distance between the survey areas were the latitude and longitude of the centroid of each polygon.

Figure 2 depicts the scatter plots of interregional trip flows and bilateral distances for the downtown areas of the largest cities in the Kansai region. Figure 2(a) shows the number of trips to the survey area around Kyoto station in Kyoto City. Figure 2(b) shows the number of trips to the survey area around Osaka station in Osaka City. Figure 2(c) shows the number of trips to the survey area around Sannomiya station in Kobe City. As Figure 2 shows, there is a negative relationship between the number of trips and the trip distance. Daily trips were less likely to involve long-distance mobility. Most trips were concentrated within a distance of 20 km.

[Table 1; Figure 1–2]

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[5] Returning home trip indicates the trip flow from locations where individuals stay outside to their residential locations. Therefore, the trip destination is the residential location, not the workplace and school locations.

[6] The great-sphere distances were calculated based on Vincenty's formula, using Stata's geodist command (Picard, 2012).

3.2. Mobile Phone Data

The second dataset on the interregional trip flows is the Mobile Spatial Statistics of NTT DOCOMO (2013), which offer big data on interregional mobility obtained by geospatial information technology, based on the locational information of mobile phone users. The MSS is based on NTT DOCOMO's mobile phone users, covering approximately 40% of the total population in Japan. Unlike the traditional survey, the Mobile Spatial Statistics estimate population distribution with fluctuation over time, 24 hours a day, and 365 days a year. The locational information is obtained from the base stations in the mobile terminal network (not mobile phone GPS).

This study employs the monthly data on inter-municipal flows from September 2015 to August 2016 by the day of the week (weekday or weekend/holiday). Detailed information on inter-municipal flows is available by gender, age, year, month, day of the week (weekdays and weekends), and time of day (4 am, 10 am, 2 pm, 8 pm).[7] In this study, the interregional trip flows are based on the residential municipalities and the municipalities where mobile phone users stayed at 2 pm.

We focus on the Kansai region, covering 245 municipalities and the wards of cities designated by government ordinance.[8] Because there are 1896 municipalities in Japan, including the 23 wards of Tokyo and wards of cities designated by government ordinance, we run 245 regressions using the inter-municipal inflows into the Kansai region from other 1895 municipalities. Thus, in total, we ran 70,560 ($= 245 \times 12 \times 2 \times 3 \times 4$) regressions of the gravity equation for each destination location j for 12 months, day type (weekday and weekend/holiday), gender (total, male, and female), and age group (total, 15–39, 40–59, and 60 and above). The same condition of internal trip distance is imposed to avoid the neighboring outliers. If the number of observations (i.e., the number of positive trip flows) is less than 10, the distance decay parameter is not estimated.

Table 2 presents the descriptive statistics on inter-municipal human mobility flows and bilateral distances regarding weekdays and weekends/holidays. The inter-municipal human mobility flows are available for each month, allowing for a dynamic trend of the regional attractiveness index. For example, seasonal events attract

[7] The dataset used in this study is freely available from the Regional Economy and Society Analyzing System (RESAS), a web application developed by the Headquarters for Overcoming Population Decline and Vitalizing Local Economy (2023) in Japan at the Prime Minister's Office.

[8] The cities designated by government ordinance are cities with populations greater than 500,000 and are designated by the government under Article 252-19 of the Local Autonomy Act. In November 2023, there are 20 cities (Sapporo, Sendai, Saitama, Chiba, Yokohama, Kawasaki, Sagamihara, Niigata, Shizuoka, Hamamatsu, Nagoya, Kyoto, Osaka, Sakai, Kobe, Okayama, Hiroshima, Fukuoka, Kitakyushu, and Kumamoto) in Japan.

more people from outside municipalities.

Figure 3 depicts the scatter plots of inter-municipal trip flows and bilateral distances for the largest cities in the Kansai region. Figure 3(a) shows the number of persons from outside Shimogyo-ku, Kyoto City. Figure 3(b) shows the number of persons from outside Kita-ku, Osaka City. Figure 3(c) shows the number of persons from outside Chuo-ku, Kobe City. In Figure 3(a), Simogyo-ku of Kyoto city attracts visitors equally on weekdays and holidays. Figures 3(b) and 3(c) show that more people from nearby municipalities enter Osaka and Kobe cities on weekdays and weekends/holidays.

[Table 2; Figure 3]

4. Results and Discussions

4.1. Application 1: Person Trip Survey Estimation Results

Table 3 presents the regional attractiveness index estimation results by trip purpose. There is a considerable heterogeneity in the distance decay parameter. Whereas the maximum values are around -2, the minimum values are around -6. These values are visualized on a map to understand the spatial distribution.

Figures 4 and 5 show the estimated regional attractiveness index from the destination-fixed gravity equation. Figure 4 depicts the spatial distribution of regional attractiveness based on the total trip flow across the Kansai region, suggesting that the downtown metropolitan areas, such as Osaka City, Kobe City, and Kyoto City, are more attractive. The total trips were disaggregated to consider how trip purposes affect regional attractiveness.

Figure 5(a) shows the spatial distribution of regional attractiveness based on people's commuting trips to their workplaces. Although downtown areas in larger cities still show higher attractiveness, some suburban areas attract people from a region-wide perspective as regional core areas.

Figure 5(b) displays the spatial distribution of regional attractiveness based on commuting trips to school. The regional attractiveness estimated from school trips is more diversified in metropolitan areas. Rural areas show missing, suggesting limited access to schools from outside.

Figures 5(c) and 5(d) show the spatial distributions of regional attractiveness based on free and business trips, respectively. In both cases, urban areas with hub stations tended to show higher attractiveness because they widely attracted people.

Figure 5(e) illustrates the spatial distribution of regional attractiveness considering the trips to returning home. Unlike commuting to the office, free, and business trips, returning home trips reveal the attractiveness of residence location. For example, Shiga and Nara prefectures attract migrants who commute to the central business district of the Kansai region. Therefore, these regions show higher regional attractiveness as living places.

Figure 5(f) shows the spatial distribution of regional attractiveness according to unknown (unclassified) trips. Although the trip purpose was unclear from the data, the regional attractiveness estimated that this type of travel would likely be concentrated in core urban areas.

[Table 3; Figures 4 and 5]

To understand the geographical distribution of regional attractiveness, this study further applies hot and cold spot analyses to the index of regional attractiveness estimated from Person Trip Survey. The standard method for hot and cold spot analyses in spatial statistics is the Getis–Ord $G_i^*(d)$ statistic, which tests whether a region and its neighboring regions form a spatial cluster.[9] Getis and Ord (1992) proposed the following statistic:

$$G_i^*(d) = \frac{\sum_{k=1}^{N} w_{ik}(d) x_k}{\sum_{k=1}^{N} x_k}, \tag{12}$$

where $w_{ik}(d)$ denotes the ijth element of the spatial weight matrix. Each element takes a binary value, as follows:

$$w_{ik}(d) = \begin{cases} 1, & \text{if } d_{ij} < d \text{ for all } i, j \\ 0, & \text{otherwise,} \end{cases} \tag{13}$$

where d is the threshold distance. In this study, the threshold distance d is set to 10 km.

The numerator of the Getis–Ord $G_i^*(d)$ statistic represents the local sum of variable x within a circle of radius d km, and the denominator represents the total sum of variable x. Therefore, those regions with higher (lower) shares of variable x are detected as hot (cold) spots. The null hypothesis is complete spatial randomness, and rejection of the null hypothesis indicates an outlier in the geographical space.

The standardized $G_i^*(d)$ can be viewed as z value of Getis–Ord $G_i^*(d)$, as follows:

$$\text{Standardized } G_i^*(d) = \frac{G_i^*(d) - \mathrm{E}[G_i^*(d)]}{\sqrt{\mathrm{Var}[G_i^*(d)]}}, \tag{14}$$

where $\mathrm{E}[G_i^*(d)]$ and $\mathrm{Var}[G_i^*(d)]$ represent the expected values and variance of $G_i^*(d)$ under the null hypothesis, respectively. The distribution of the standardized $G_i^*(d)$ approaches a standard normal distribution as N approaches infinity. When the standardized $G_i^*(d)$ takes a positive (negative) value and falls within the critical region, region i is identified as a hot (cold) spot. The critical values for hot and cold

[9] The Stata's getisord command is used to calculate the Getis–Ord $G_i^*(d)$ statistic (Kondo, 2016).

spots are approximately ± 1.96 and ± 2.58 at the 5% and 1% significance levels, respectively.

Figures 6 and 7 show the results of the hot and cold spot analyses based on the estimation results in Figures 4 and 5. Generally, the largest cities in the Kansai region, namely Kyoto, Osaka, and Kobe, tend to show hotspots of regional attractiveness. However, the estimation results provide important insights into regional attractiveness. For example, Figure 7(e) shows that there are hotspots of regional attractiveness estimated from returning home trips in Shiga and Nara prefectures, suggesting that these areas are likely to be convenient for commuting to work and travel, given their accessibility to public transportation.

In sum, the empirical results of this study have significant implications for regional attractiveness. While urban centers are generally considered attractive, regional attractiveness is not time-invariant. The attractiveness of a trip destination depends on the purpose of the trip. As human mobility data becomes more readily available in the era of Big Data, it is crucial to monitor changes in regional attractiveness continuously.

[Figures 6–7]

4.2. Application 2: Mobile Phone Data Estimation Results

Table 4 presents the regional attractiveness index estimated from the mobile phone data. Figure 8 visualizes the distribution of the regional attractiveness index by month. We found considerable heterogeneity in the distance decay parameter; the maximum values are around -1, whereas the minimum values are around -5. Seasonal fluctuations are also found. These values are visualized on a map and in time-series lines.

[Table 4; Figure 8]

Figure 9 shows the geographic distribution of the regional attractiveness index in June 2016 (weekday) and August 2016 (weekend/holiday), estimated from the inter-municipal human mobility data collected from mobile phone users. Exploiting the advantage of the high-frequency big data, this study estimates the regional attractiveness indices across months, day type (weekday and weekend/holiday), gender (total, male, and female), and age group (total, 15–39, 40–59, and 60 and above). All results are shown on the web app.

Figure 9 shows an index trend similar to Figure 4, although different data are used. Osaka City shows a higher attractiveness of trip destinations. A comparison between Figures 9(a) and 9(b) provides an interesting result regarding seasonal factors. Whereas municipalities with a high regional attractiveness index were concentrated in the central business district in June 2016, rural municipalities showed higher values of the regional attractiveness index in August 2016 during the summer vacation. These findings suggest that the attractiveness of trip destinations dynamically fluctuates throughout the year.

Figures 10–12 show the seasonal trends in the regional attractiveness index for selective cities in the Kansai region regarding weekdays and weekends/holidays. Figure 10 shows that Higashiyama-ku, Kyoto

City, always attracts people, irrespective of weekdays and weekends/holidays, because of its abundant tourism resources.

Figure 11 shows that Konohana-ku, Osaka City, attracts people seasonally because of its world-famous amusement facility. The regional attractiveness index based on mobile phone data shows the highest value in the Kansai region. In the winter and spring vacation seasons, there is a high influx of visitors even on weekdays. The same trend is not seen for seniors, suggesting that this area is more attractive to the young generations, including families with kids.

Figure 12 shows that Nishinomiya City attracts more people in March and August because well-known high school baseball tournaments are held in Koshien Stadium. Although the average regional attractiveness index of Nishinomiya city lies between -1.6 and -2.0, this value becomes -1.2 in August 2016.

The empirical results from the mobility big data have significant implications. The attractiveness of the trip destination shows seasonality throughout the year. Although drawing intuitive implications from the raw OD flow data is difficult because of the two-dimensional network data, the novel approach proposed in this study successfully addresses the complexity of using human mobility data by reducing the dimension to a single scalar. The ESDA, using the estimated regional attractiveness index, contributes to understanding the spatial structure of the attractiveness of trip destinations.

[Figures 9–12]

5. Conclusion

This study proposed a scalar index of regional attractiveness based on bilateral human mobility flows. Given that individuals' trip choice is generally based on utility maximization, this study assumes that trip flows include fundamental information on the attractiveness of trip destinations. Revisiting the original idea of Baxter (1979), this study discussed that a destination-fixed gravity equation provides a simple framework for estimating the heterogeneous attractiveness of each trip destination. This empirical analysis based on the Person Trip Survey in the Kansai region of Japan provided insights into how regional attractiveness depends on different mobility purposes. The empirical results of mobile phone data revealed the attractiveness of trip destinations fluctuates seasonally throughout the year.

This study has some limitations. Although the regional attractiveness index plays a key role as a monitoring indicator of local economic vitalization and provides a new view for the ESDA, it is also essential to explore how and what factors increase regional attractiveness. For example, regions with hub stations constantly attract passengers from other regions. Some local populous events increase the number of temporal trips, leading to a temporal increase in regional attractiveness. In this case, the synthetic control method may be useful to evaluate the causal impact on the attractiveness of a trip destination. Therefore, statistical analysis for examining which factors increase regional attractiveness is essential to understand local economic performance deeply. These challenges need to be tackled in future research.

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Author Contributions

Keisuke Kondo: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Funding acquisition.

Declaration of Competing Interest

The author declares no competing interests.

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Supplementary Information

The web app, which provides full estimation results in this study, is available on the following webpage (URL: https://keisuke-kondo.shinyapps.io/regional-attractiveness-kansai/).

Figure 1. Kansai region of Japan

Note: Author's creation. The 2010 Person Trip Survey conducted in the Kansai region covers six prefectures (Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama). The Mobile Spatial Statistics of NTT DOCOMO covers the entire area of Japan, but this study focuses on the same region as the 2010 Person Trip Survey. The locations of the cities discussed in this paper are shown on the map. Higashiyama-ku, Kyoto city has many historical tourist resources and attract many visitors throughout the year. Konohana-ku, Osaka city has one of the most popular amusement parks, the Universal Studios Japan. High school baseball at Koshien Staduim in Nishinomiya-city is one of the most popular sport evens in Japan.

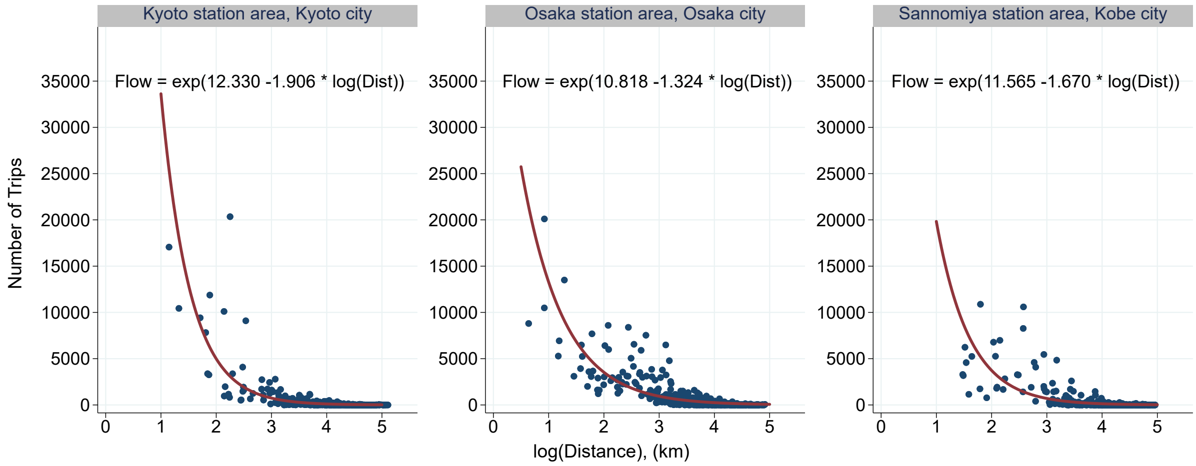
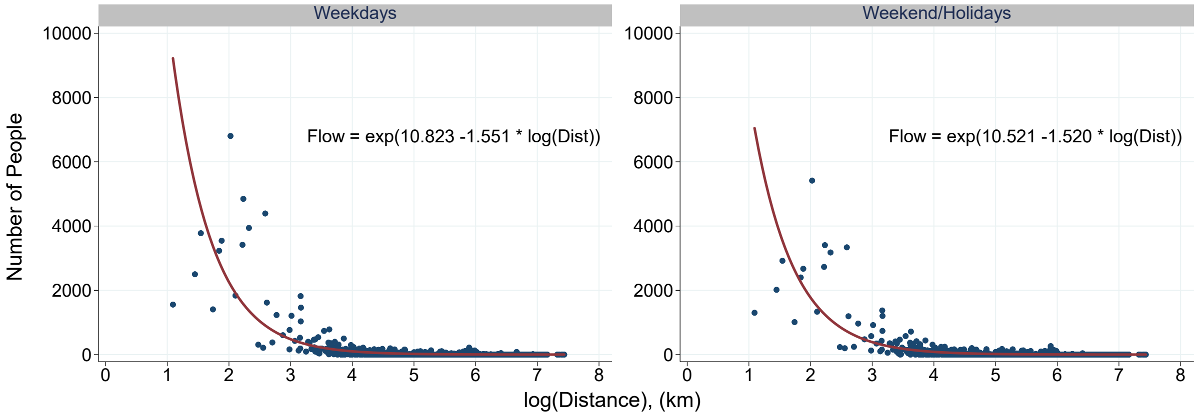
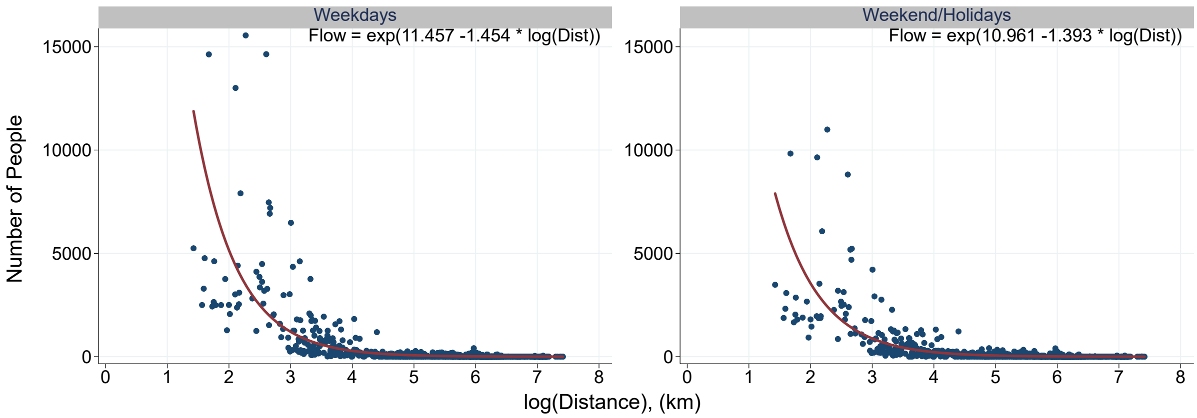


Figure 2. Scatter Plots of the Number of Total Trips and Bilateral Distance from Person Trip Survey

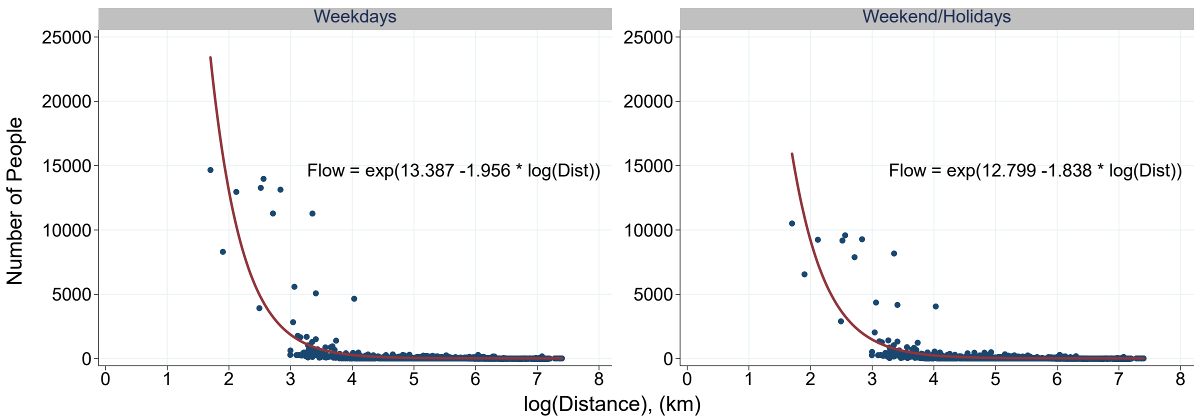
Note: Author's creation. Trip flows within the diameter of each area are excluded as internal trip flows. The zone codes of Kyoto, Osaka, and Sannomiya station areas, defined in the Person Trip Survey, are 31230, 51110, and 71230, respectively.



(a) Kyoto station area, Simogyo-ku, Kyoto city (Municipal code: 26106)



(b) Osaka station area, Kita-ku, Osaka city (Municipal code: 27127)



(c) Sannomiya station area, Chuo-ku, Kobe city (Municipal code: 28110)

Figure 3. Scatter Plots of the Number of People and Bilateral Distance from Mobile Phone Data

Note: Author's creation. Trip flows within the diameter of each area are excluded as internal trip flows. Total flows for all people in August 2016 are visualized.

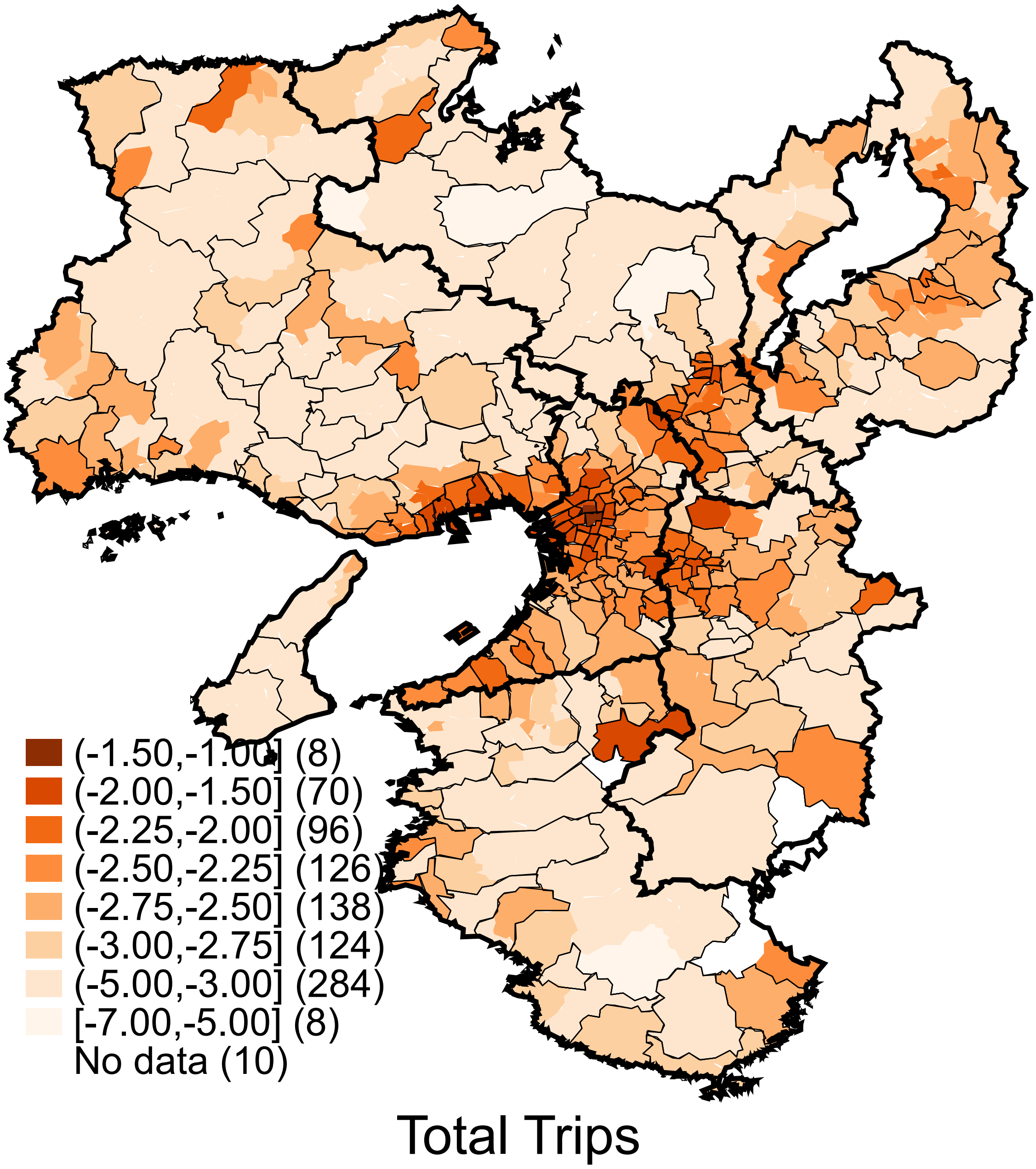


Figure 4. Regional Attractiveness Index from Person Trip Survey

Note: Author's creation.

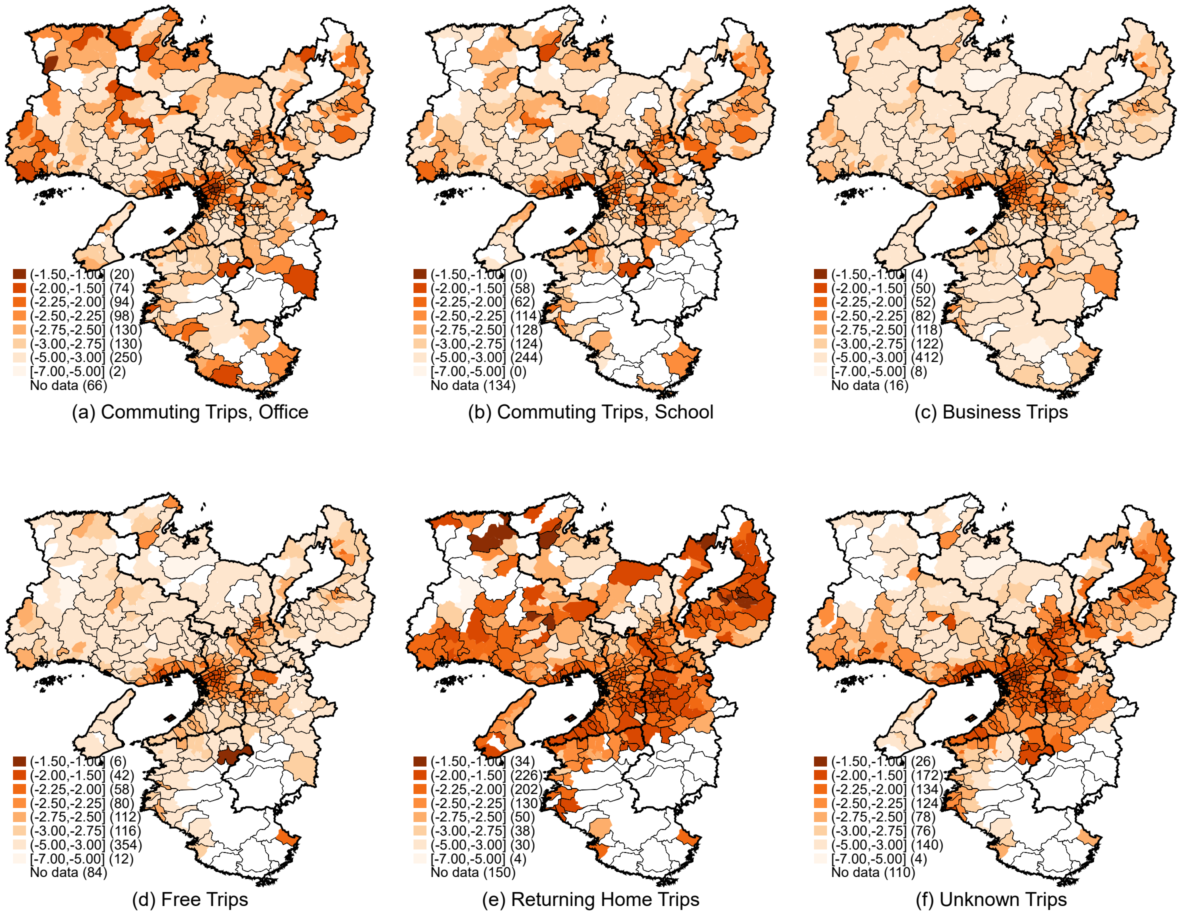


Figure 5. Regional Attractiveness Index by Trips Purpose from Person Trip Survey

Note: Author's creation.

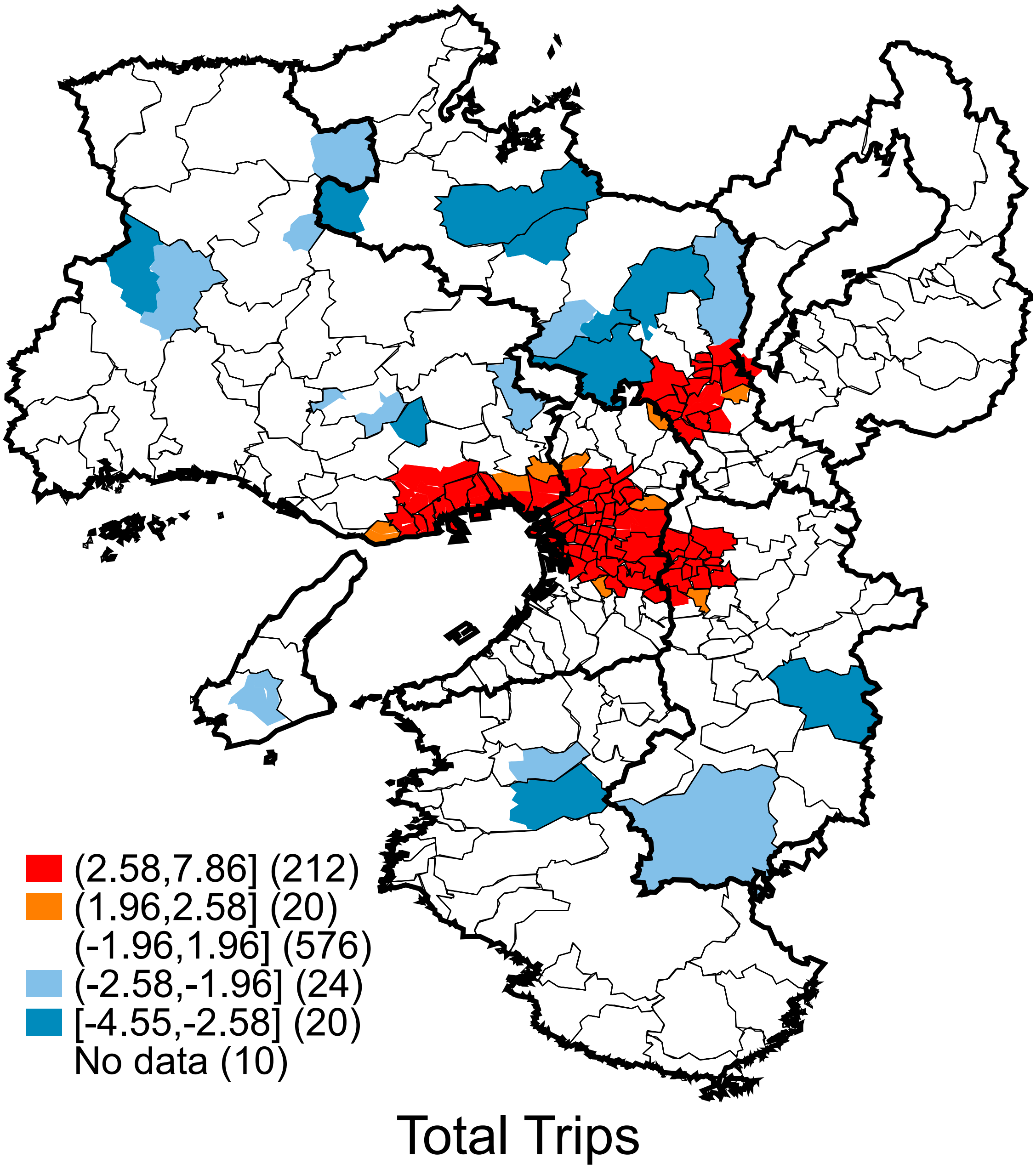


Figure 6. Hot and Cold Spots of Regional Attractiveness Index for Total Trips from Person Trip Survey

Note: Author's creation. The threshold distance d is set to 10 km.

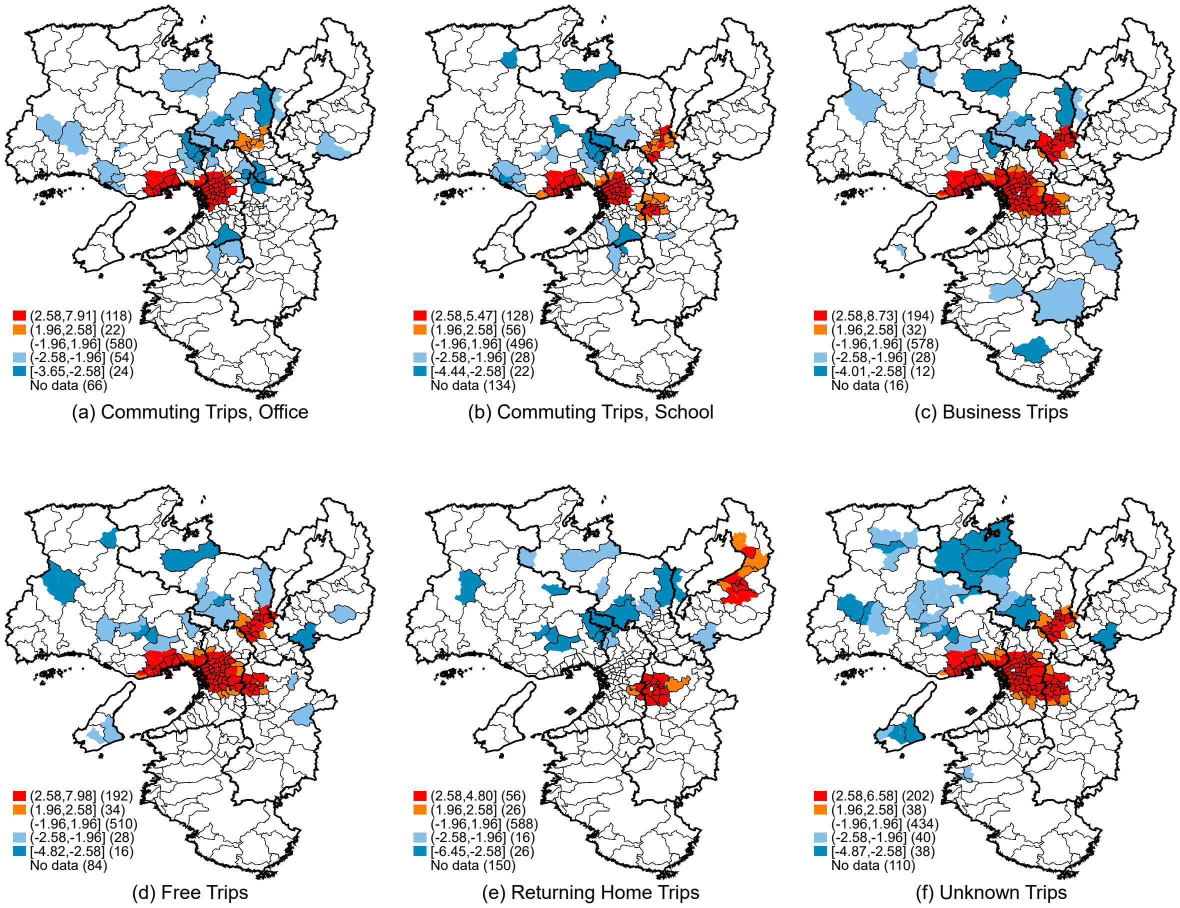


Figure 7. Hot and Cold Spots of Regional Attractiveness Index by Trip Purpose from Person Trip Survey

Note: Author's creation. The threshold distance d is set to 10 km.

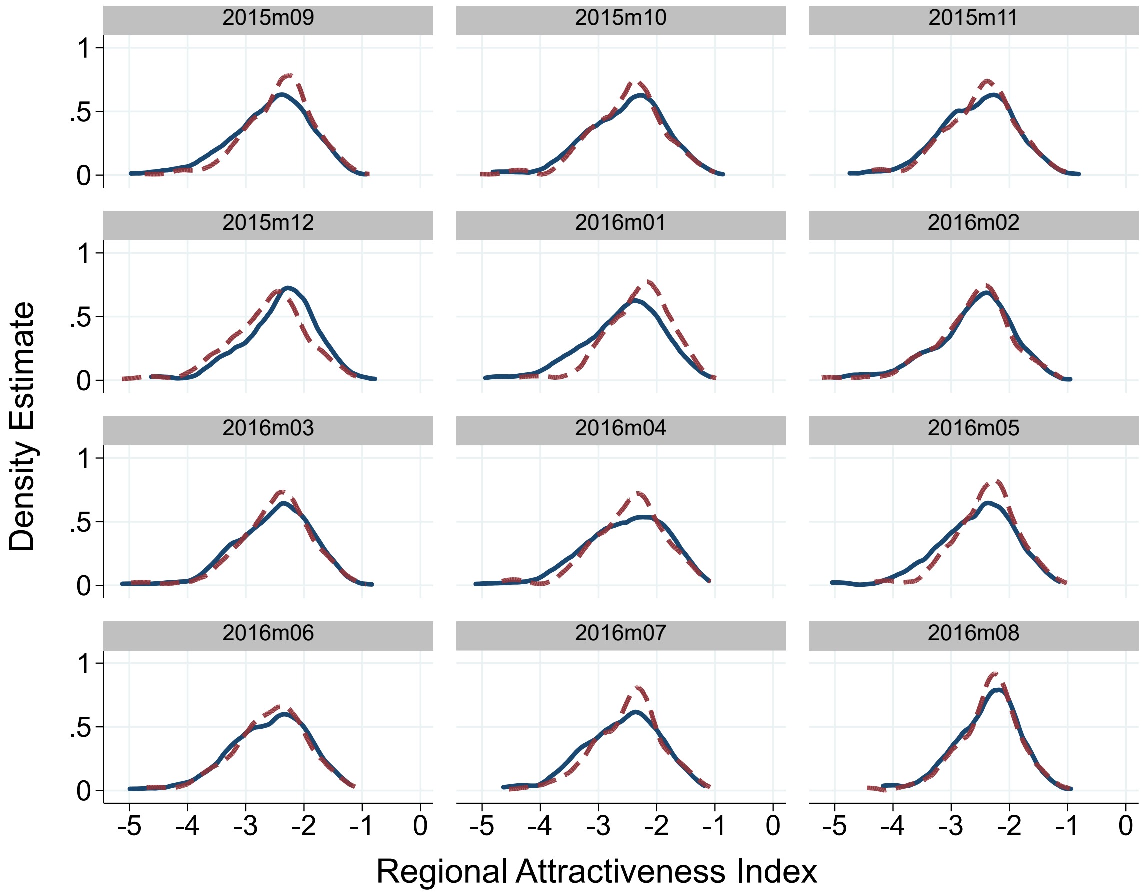
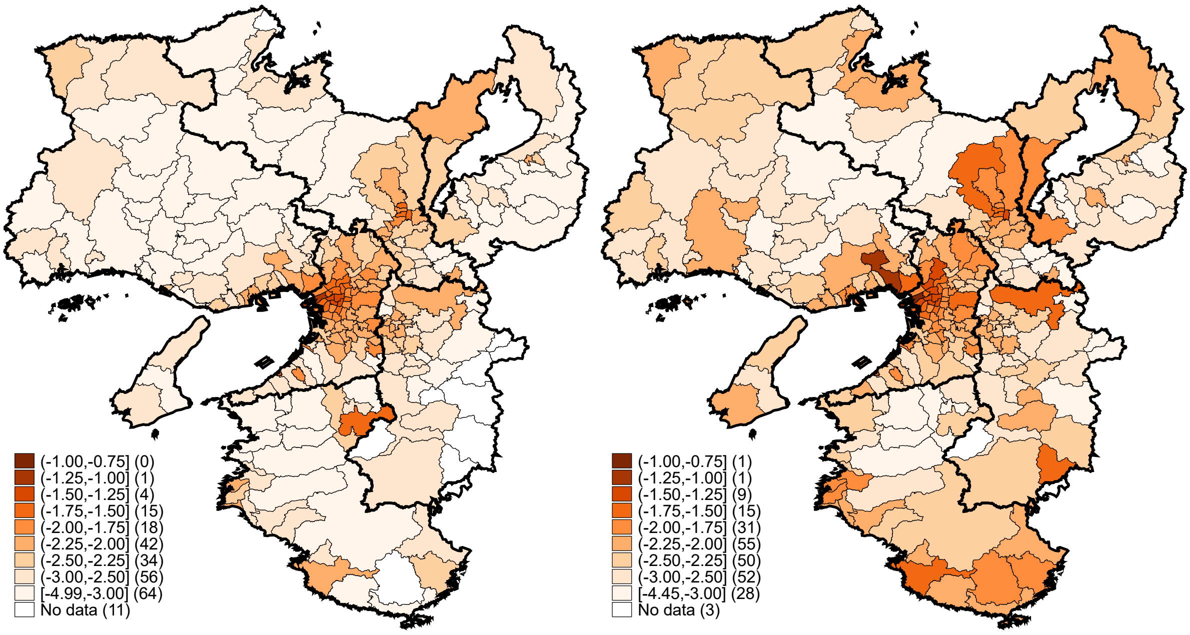


Figure 8. Distribution of Regional Attractiveness Index from Mobile Phone Data

Note: Author's creation. Estimation results from the dataset of gender (total) and age group (total) are shown.



(a) On Weekdays in June 2016 (b) On Weekends/Holidays in August 2016

Figure 9. Geographic Distribution of Regional Attractiveness Index from Mobile Phone Data

Note: Author’s creation. Estimation results from the dataset of gender (total) and age group (total) are shown.

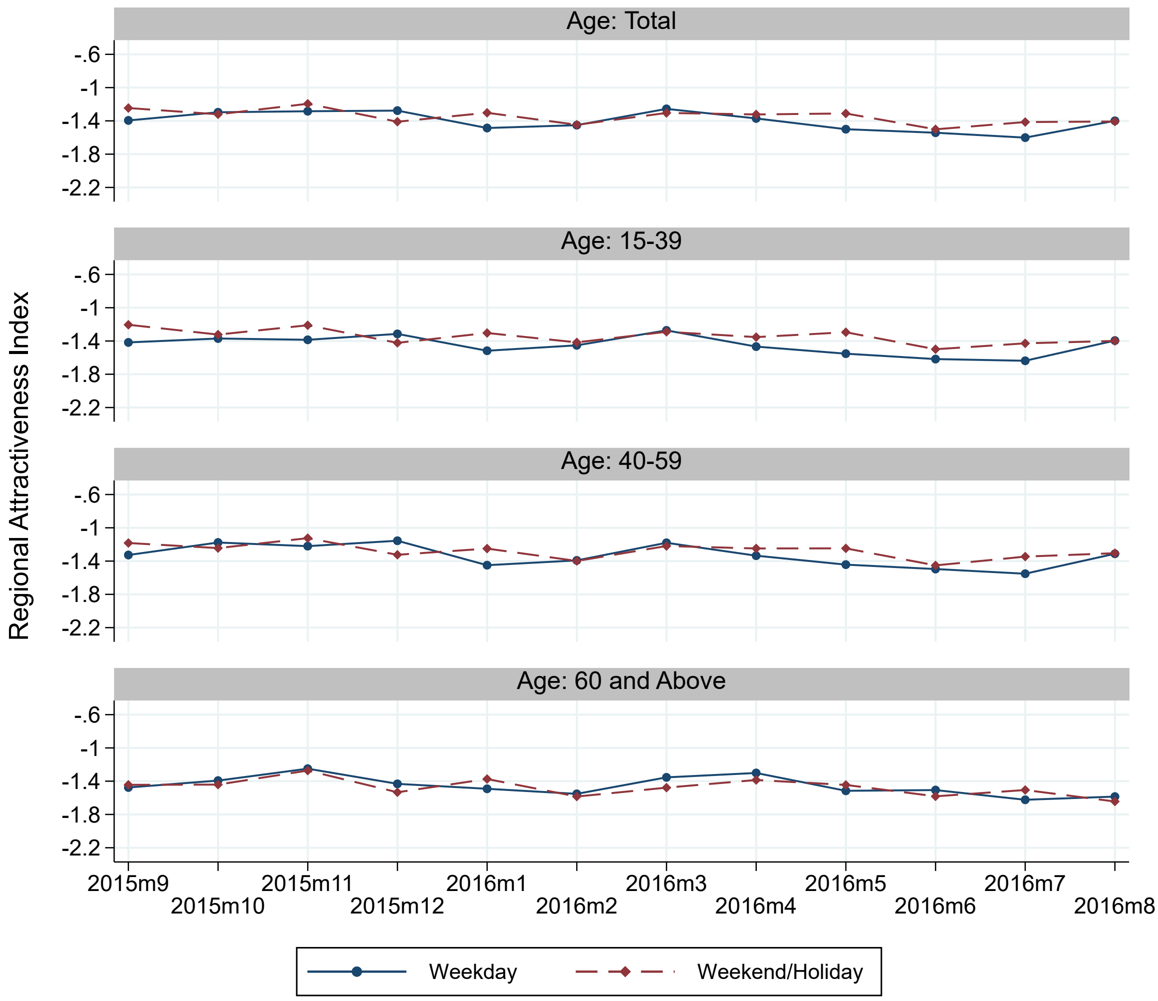


Figure 10. Dynamic Trend of Regional Attractiveness Index in Higashiyama-ku, Kyoto city, Kyoto

Note: Author's creation. The data above are based on the estimation results of gender (total).

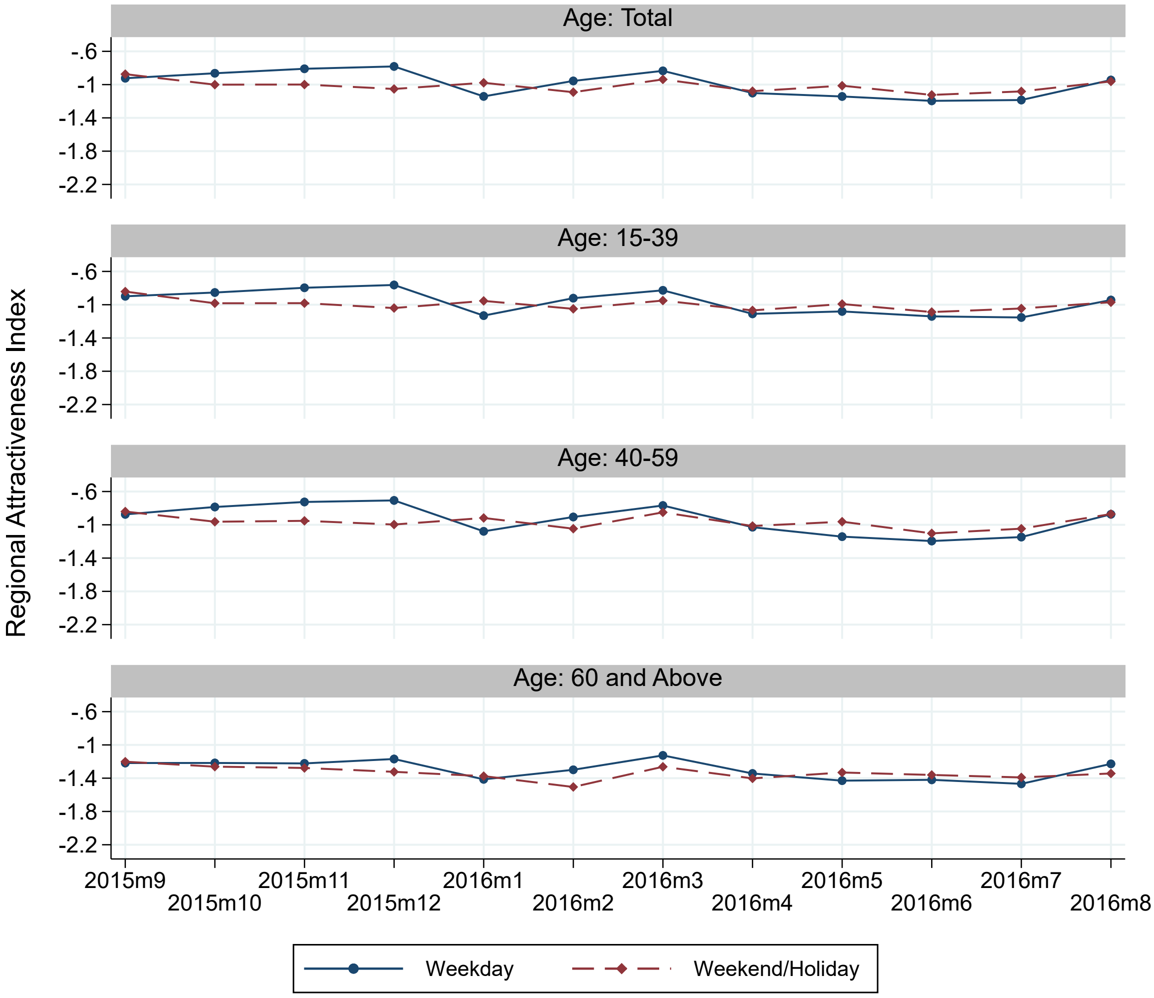


Figure 11. Dynamic Trend of Regional Attractiveness Index in Konohana-ku, Osaka city, Osaka

Note: Author’s creation. The data above are based on the estimation results of gender (total).

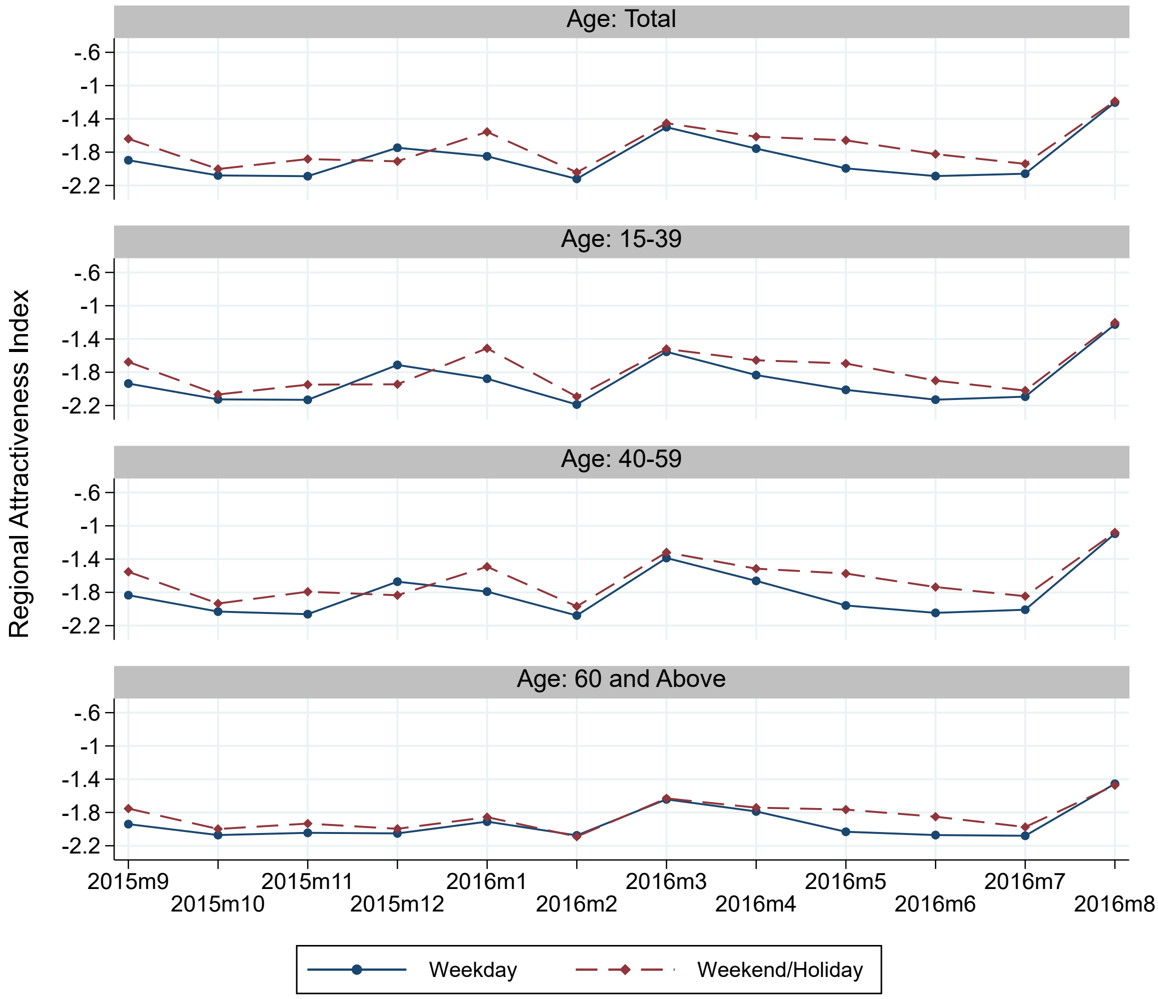


Figure 12. Dynamic Trend of Regional Attractiveness Index in Nishinomiya city, Hyogo

Note: Author's creation. The data above are based on the estimation results of gender (total).

Table 1. Descriptive Statistics of Trip Flows from Person Trip Survey

Variables	Obs	Mean	S.D.	Min	P10	P50	P90	Max
Number of Trips (Total)	40,767	81.89	563.51	0	0	0	91	36,938
Number of Trips (Office)	23,468	23.54	206.39	0	0	0	24	15,189
Number of Trips (School)	17,956	16.35	166.12	0	0	0	0	13,892
Number of Trips (Free)	21,359	19.38	150.74	0	0	0	19	10,761
Number of Trips (Business)	28,003	34.93	283.64	0	0	0	39	23,821
Number of Trips (Returning Home)	20,714	20.84	159.96	0	0	0	18	7,815
Number of Trips (Unknown)	30,071	46.46	280.30	0	0	0	55	14,603
Distance (km)	184,932	80.53	43.36	1.88	27.04	76.09	139.56	261.44

Note: The unit of observation is the trip flow between survey zones. The total number of interregional trip flows is 186,192 ($= 432 \times 432 - 432$), and the gravity equation is estimated after excluding the intra-municipal flows. Obs represents the positive trip flows between survey zones.

Table 2. Descriptive Statistics of Trip Flows from Mobile Phone Data

Variables	Obs	Mean	S.D.	Min	P10	P50	P90	Max
Weekdays								
Number of People (Sep 2015)	26,205	9.87	142.14	0	0	0	0	16,053
Number of People (Oct 2015)	26,392	10.33	144.66	0	0	0	0	15,970
Number of People (Nov 2015)	25,109	10.22	145.00	0	0	0	0	15,862
Number of People (Dec 2015)	28,998	10.07	134.98	0	0	0	0	15,315
Number of People (Jan 2016)	25,354	9.77	140.36	0	0	0	0	15,652
Number of People (Feb 2016)	23,102	9.41	140.98	0	0	0	0	16,195
Number of People (Mar 2016)	27,540	9.90	141.36	0	0	0	0	16,631
Number of People (Apr 2016)	28,737	10.50	144.80	0	0	0	0	15,988
Number of People (May 2016)	24,428	10.02	143.97	0	0	0	0	15,761
Number of People (Jun 2016)	23,436	10.06	146.11	0	0	0	0	16,127
Number of People (Jul 2016)	23,191	9.84	144.15	0	0	0	0	16,392
Number of People (Aug 2016)	30,822	10.11	133.51	0	0	0	0	15,552
Weekends/Holidays								
Number of People (Sep 2015)	27,310	8.26	99.03	0	0	0	0	11,438
Number of People (Oct 2015)	24,042	7.86	101.31	0	0	0	0	11,852
Number of People (Nov 2015)	24,886	8.05	101.72	0	0	0	0	12,051
Number of People (Dec 2015)	21,235	7.30	103.78	0	0	0	0	12,710
Number of People (Jan 2016)	29,386	8.09	94.35	0	0	0	0	11,132
Number of People (Feb 2016)	20,299	6.84	97.38	0	0	0	0	11,712
Number of People (Mar 2016)	24,875	7.79	102.32	0	0	0	0	12,390
Number of People (Apr 2016)	25,880	8.13	103.77	0	0	0	0	12,018
Number of People (May 2016)	27,507	8.36	100.18	0	0	0	0	11,789
Number of People (Jun 2016)	21,248	7.41	102.21	0	0	0	0	12,420
Number of People (Jul 2016)	24,115	7.73	100.39	0	0	0	0	12,239
Number of People (Aug 2016)	27,840	7.88	92.32	0	0	0	0	10,992
Distance (km)	463,372	447.35	325.62	2.13	88.92	393.20	1029.38	1761.97

Note: The unit of observation is the trip flow between municipalities. The total number of inter-municipal flows is 464,275 ($= 245 \times 1896 - 245$), and the gravity equation is estimated after excluding the intra-municipal flows. Obs represents the positive trip flows between municipalities. The data above are based on the estimation results of gender (total) and age group (total).

Table 3. Descriptive Statistics of Regional Attractiveness Index from Person Trip Survey

Variables	Obs	Mean	S.D.	Min	P10	P50	P90	Max
Regional Attractiveness Index (Total)	427	-2.78	0.65	-5.75	-3.57	-3.15	-2.73	-2.32
Regional Attractiveness Index (Office)	399	-2.73	0.65	-5.40	-3.55	-3.11	-2.71	-2.29
Regional Attractiveness Index (School)	365	-2.78	0.56	-4.82	-3.45	-3.15	-2.75	-2.40
Regional Attractiveness Index (Free)	390	-3.03	0.77	-6.73	-3.96	-3.47	-2.95	-2.52
Regional Attractiveness Index (Business)	424	-3.04	0.72	-6.24	-3.89	-3.47	-3.00	-2.55
Regional Attractiveness Index (Home)	357	-2.17	0.50	-5.41	-2.75	-2.36	-2.09	-1.89
Regional Attractiveness Index (Unknown)	377	-2.46	0.67	-5.75	-3.39	-2.83	-2.33	-1.97

Note: The unit of observation is the municipality. Some municipalities have no value because of an insufficient number of positive trip flows. The data above are based on the estimation results of gender (total) and age group (total).

Table 4. Descriptive Statistics of Regional Attractiveness Index from Mobile Phone Data

Variables	Obs	Mean	S.D.	Min	P10	P50	P90	Max
Weekdays								
Regional Attractiveness Index (Sep 2015)	233	-2.57	0.68	-4.97	-3.46	-2.50	-1.75	-0.92
Regional Attractiveness Index (Oct 2015)	234	-2.54	0.67	-4.81	-3.45	-2.43	-1.74	-0.86
Regional Attractiveness Index (Nov 2015)	233	-2.54	0.64	-4.74	-3.38	-2.43	-1.74	-0.81
Regional Attractiveness Index (Dec 2015)	233	-2.42	0.63	-4.62	-3.28	-2.31	-1.70	-0.78
Regional Attractiveness Index (Jan 2016)	231	-2.58	0.69	-4.94	-3.51	-2.49	-1.78	-1.07
Regional Attractiveness Index (Feb 2016)	230	-2.63	0.69	-5.00	-3.56	-2.51	-1.80	-0.96
Regional Attractiveness Index (Mar 2016)	234	-2.52	0.65	-5.12	-3.36	-2.45	-1.74	-0.83
Regional Attractiveness Index (Apr 2016)	234	-2.54	0.70	-5.11	-3.50	-2.46	-1.69	-1.10
Regional Attractiveness Index (May 2016)	233	-2.57	0.66	-5.04	-3.41	-2.48	-1.80	-1.14
Regional Attractiveness Index (Jun 2016)	234	-2.60	0.66	-4.99	-3.45	-2.54	-1.82	-1.20
Regional Attractiveness Index (Jul 2016)	234	-2.60	0.65	-4.63	-3.49	-2.54	-1.80	-1.19
Regional Attractiveness Index (Aug 2016)	241	-2.38	0.55	-4.17	-3.07	-2.31	-1.77	-0.94
Weekends/Holidays								
Regional Attractiveness Index (Sep 2015)	239	-2.42	0.58	-4.74	-3.15	-2.35	-1.72	-0.87
Regional Attractiveness Index (Oct 2015)	236	-2.52	0.63	-5.03	-3.34	-2.43	-1.74	-1.00
Regional Attractiveness Index (Nov 2015)	238	-2.49	0.60	-4.36	-3.27	-2.40	-1.75	-1.00
Regional Attractiveness Index (Dec 2015)	233	-2.62	0.66	-5.13	-3.47	-2.54	-1.86	-1.05
Regional Attractiveness Index (Jan 2016)	237	-2.31	0.56	-4.36	-2.97	-2.22	-1.62	-0.98
Regional Attractiveness Index (Feb 2016)	230	-2.63	0.68	-5.22	-3.51	-2.52	-1.89	-1.09
Regional Attractiveness Index (Mar 2016)	235	-2.50	0.63	-4.97	-3.25	-2.43	-1.76	-0.94
Regional Attractiveness Index (Apr 2016)	233	-2.49	0.62	-4.66	-3.29	-2.43	-1.70	-1.08
Regional Attractiveness Index (May 2016)	241	-2.40	0.55	-4.31	-3.09	-2.33	-1.74	-1.01
Regional Attractiveness Index (Jun 2016)	234	-2.58	0.63	-4.70	-3.43	-2.54	-1.80	-1.12
Regional Attractiveness Index (Jul 2016)	237	-2.50	0.59	-4.54	-3.24	-2.42	-1.77	-1.08
Regional Attractiveness Index (Aug 2016)	242	-2.35	0.54	-4.45	-3.01	-2.30	-1.72	-0.96

Note: The unit of observation is the municipality. Some municipalities have no value because of an insufficient number of positive trip flows. The data above are based on the estimation results of gender (total) and age group (total).

Online Appendix

Measuring the attractiveness of trip destinations: A study of the Kansai region of Japan

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Appendix A. Web Application

This study provides a web application that visualizes the estimated regional attractiveness index in the Kansai region of Japan. Figure A.1 shows a map visualization system of regional attractiveness index. Figure A.2 shows the time-series visualization estimated from the human flow big data.

[Figures A.1–A.2]

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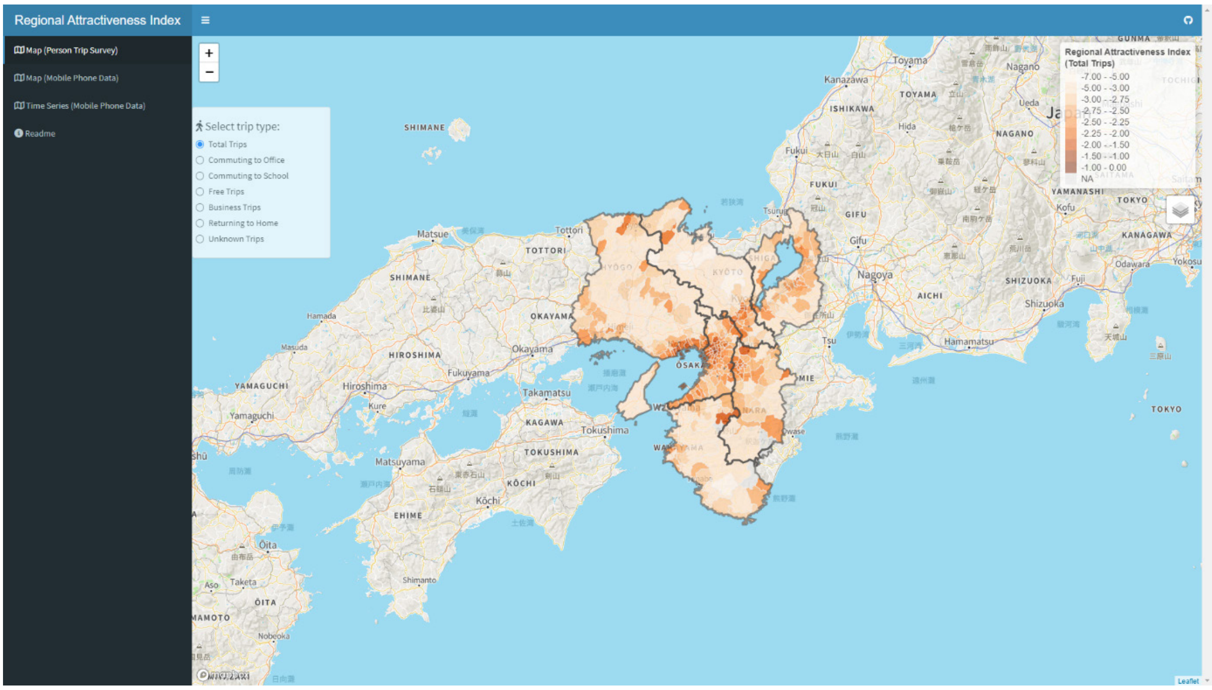
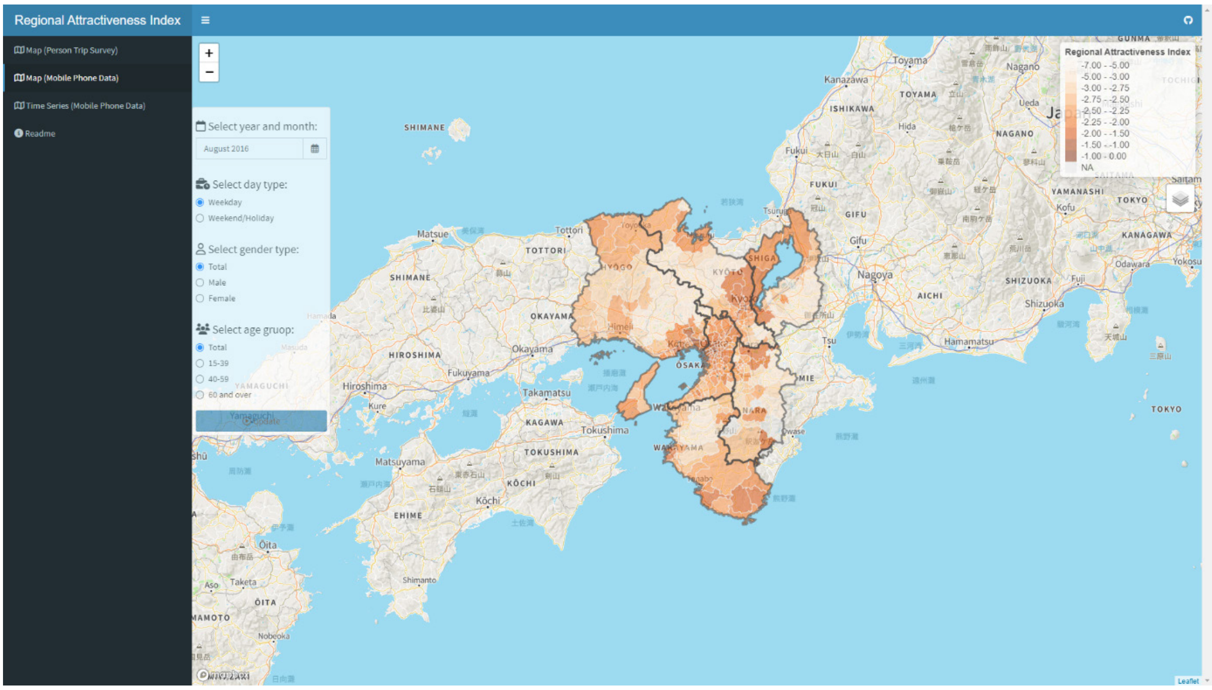


(a) Person Trip Survey Estimation Results



(b) Mobile Phone Data Estimation Results

Figure A.1. Visualizing Regional Attractiveness Index on Map

Note: Screenshot from https://keisuke-kondo.shinyapps.io/regional-attractiveness-kansai/ (accessed April 4, 2024).

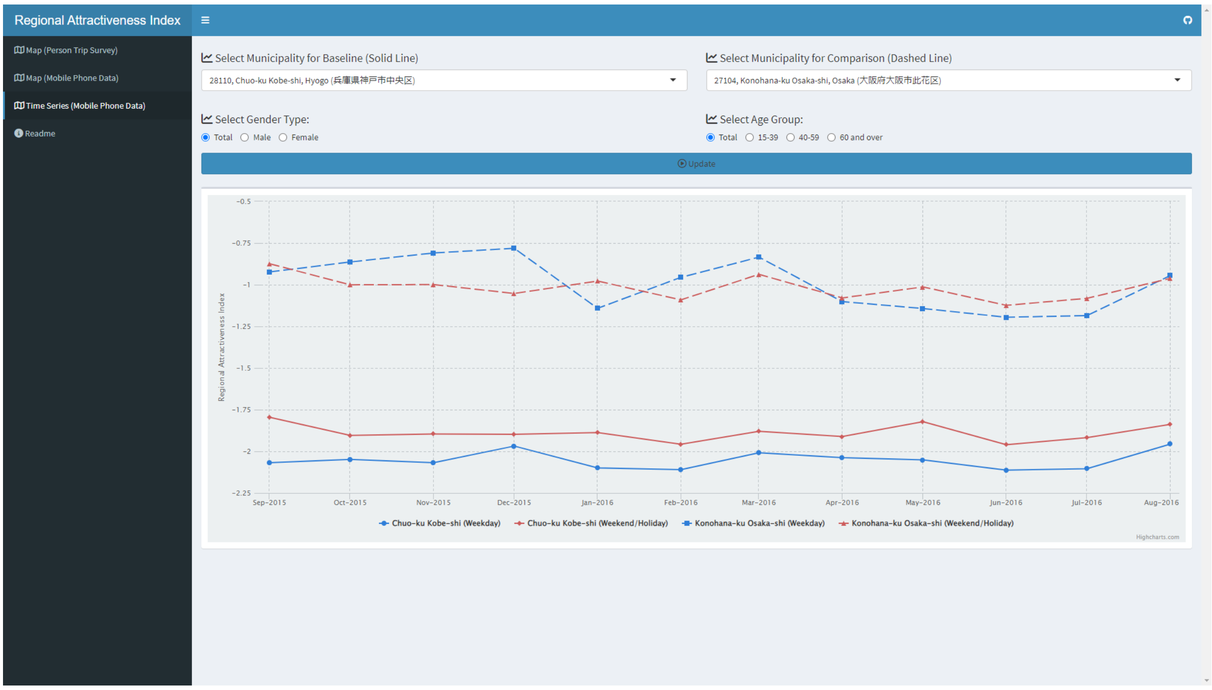


Figure A.2. Time-Series Visualization for Regional Attractiveness Index

Note: Screenshot from https://keisuke-kondo.shinyapps.io/regional-attractiveness-kansai/ (accessed April 4, 2024).