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Unravel the landscape and pulses of cycling activities from a dockless bike-sharing system

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ABSTRACT

The recent boom of sharing economy along with its technological underpinnings have brought new opportunities to urban transport ecosystems. Today, a new mobility option that provides station-less bike rental services is emerging. While previous studies mainly focus on analyzing station-based systems, little is known about how this new mobility service is used in cities. This research proposes an analytical framework to unravel the landscape and pulses of cycling activities from a dockless bike-sharing system. Using a four-month GPS dataset collected from a major bike-sharing operator in Singapore, we reconstruct the temporal usage patterns of shared bikes at different places and apply an eigendecomposition approach to uncover their hidden structures. Several key built environment indicators are then derived and correlated with bicycle usage patterns. According to the analysis results, cycling activities on weekdays possess a variety of temporal profiles at both trip origins and destinations, highlighting substantial variations of bicycle usage across urban locations. Strikingly, a significant proportion of these variations is explained by the cycling activeness in the early morning. On weekends, the overall variations are much smaller, indicating a more uniform distribution of temporal patterns across the city. The correlation analysis reveals the role of shared bikes in facilitating the first- and last-mile trips, while the contribution of the latter (last-mile) is observed to a limited extent. Some built environment indicators, such as residential density, commercial density, and number of road intersections, are correlated with the temporal usage patterns. While others, such as land use mixture and length of cycling path, seem to have less impact. The study demonstrates the effectiveness of eigendecomposition for uncovering the system dynamics. The workflow developed in this research can be applied in other cities to understand this new-generation system as well as the implications for urban design and transport planning.

1. Introduction

In the past few decades, with increasing concerns over global warming and rapid urbanization, numerous efforts have been devoted in cities to advance public bike sharing as a viable and green mobility solution. Bike-sharing systems allow citizens' short-term access to bicycles, when needed, without bearing the cost and responsibilities of bike ownership. The successful implementation of bike-sharing systems could provide alternative solutions to many urban issues, such as traffic congestion, air pollution, energy deficiency, and deterioration of human health (DeMaio, 2009; Jäppinen, Toivonen, & Salonen, 2013; W. H. Organization, 2002).

Since 1965, bike-sharing systems have evolved through several key phases. The first bike-sharing program, the White Bikes, was initiated in Amsterdam as dockless and free (DeMaio, 2009; Shaheen, Guzman, & Zhang, 2010). However, its implementation sustained for a short while due to bike theft and vandalism. In order to better manage bikes and improve service stability, later generations of bike-sharing system require users to pick up and drop off bikes at fixed locations. Such bike-sharing systems with docking stations quickly spread across cities and

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successfully promoted cycling activities. However, the stability offered by docking stations came with limited accessibility of bikes and flexibility for users (Fishman, Washington, Haworth, & Mazzei, 2014). The deployment of bikes was also limited by the available space for docking stations, particularly in condensed cities.

The recent boom of sharing economy along with its technological underpinnings have brought new opportunities to the bike-sharing markets. Today, a new type of system that provides station-less bike rental services is expanding (iiMedia Research, 2017; Zhang, Shaheen, & Chen, 2014). Many cities nowadays are implementing this new generation system, which allows people to locate and unlock a bicycle using a smart-phone app, and then leave the bike wherever the journey ends. These new services are quickly adopted by citizens, who view them as a healthy and cost-effective mobility solution, or simply a kind of fashion.

Previous studies have mainly focused on examining the utilization of station-based systems (Froehlich, Neumann, Oliver, et al., 2009; Vogel, Greiser, & Mattfeld, 2011). Little is known, however, about the usage of this new generation bike-sharing scheme. As bicycles are unleashed from docking stations, users will have more freedom to choose where to start and end their trips. The spatiotemporal patterns of cycling activities induced by the dockless systems may be quite different from traditional ones with fixed rental stations. To date, limited studies have examined the usage of dockless bike-sharing systems in cities (Bao, He, Ruan, Li, & Zheng, 2017; Shen, Zhang, & Zhao, 2018). These studies focused more on analyzing the intensity of cycling activities and their spatial distributions. How travel demand changes over time at different locations and how these temporal signatures vary among places were not investigated.

This study aims to unravel the landscape and pulses of cycling activities from a dockless bike-sharing system. Using a four-month GPS dataset collected from a major bike-sharing operator in Singapore, we reconstruct the temporal usage patterns of shared bikes across urban locations based on millions of cycling trips extracted from the dataset. An eigendecomposition approach is then employed to uncover the hidden structures of these temporal patterns by revealing how they resemble or deviate from the base mode (average pulse) of the city. Then, several key built environment indicators are derived and correlated with bicycle usage patterns. Finally, we visualize the spatial distribution of places with distinctive temporal signatures to gain location-specific insights.

The paper is organized as follows. Section 2 provides a comprehensive review on the evolution of bike-sharing systems and relevant research. Section 3 describes the dataset and study area, followed by detailed descriptions of methodologies. Results are then presented and analyzed in Section 4. Finally, in Section 5, we conclude our study and discuss future research directions.

2. Literature review

2.1. History of bike sharing

The conventional bike-sharing programs have gone through three stages as summarized in (DeMaio, 2009; Shaheen et al., 2010). The first bike-sharing program, the White Bikes, was introduced in Amsterdam in the 1960s where all bikes were offered unlocked and free-of-charge. Its implementation sustained for a short time mainly due to bike theft and vandalism. The following coin-deposit generation in 1990s introduced docking stations and required users to pay a small amount of deposit before initiating trips at a particular station. Due to the anonymous nature of payment and the lack of tracking technology, such systems also suffered from instability of services due to bike theft, because one can simply appropriate the bikes after paying for the deposit. The third generation of bike-sharing system is known as the information technology (IT) based system. The IT-based system has equipped with many new technologies such as mag-stripe cards and mobile phone access. This system quickly spread across cities around the globe and successfully promoted cycling activities (Handy, Heinen, & Krizek, 2012; Larsen, 2013; Pucher, Lanversin, Suzuki, & Whitelegg, 2012). By 2010, there are 101 bike-sharing programs worldwide with 139,300 bikes and 9,332 stations. However, its accessibility and scale of development as well as users' flexibility were constrained by the locations and sizes of docking stations (Fishman, Washington, & Haworth, 2014; Fishman, Washington, Haworth, & Mazzei, 2014). It was until recently, with the prevalence of mobile phones and mobile payment, that the invention of dockless systems fully unleashed the potential of urban bike sharing. In 2015, Ofo and Mobike, two start-up companies in China, introduced a new generation of fully dockless bike-sharing system. In this system, bikes are embedded with GPS sensors and users can locate and unlock bikes with a smartphone app and later pay for it using mobile payment. Unrestrained by the docking stations, users can reach wider destination and this system has expanded tremendously in the recent two years. By March 2017, there have been over 4 million dockless bikes deployed in China while there were only 180,000 in February 2012 (iiMedia Research, 2017; Zhang et al., 2014). This system has also spread to Hong Kong, Singapore, and cities in western countries.

2.2. Spatiotemporal analysis of bike sharing

Spatiotemporal analysis of bike-sharing data (stock or trip data) can provide evidence for service monitoring and optimization. Most of the docked bike-sharing studies have access only to the stock data that tracks the variation in the number of available bikes, while the trip data, which include origins and destinations, reveal more information of the service. To analyze stock data, clustering techniques are usually adopted to categorize stations that share similar behaviors. The temporal profile of normalized available bikes is calculated for clustering. Clustering was employed to identify three clusters in Dublin's bike-sharing system namely attractor, generator and balanced stations in (Jiménez, Nogal, Caulfield, & Pilla, 2016). Similarly, Froehlich et al. found six clusters that share similar temporal patterns of bike usage from Bicing, a bike-sharing system in Barcelona, and studied how these relate to the neighborhood and time of day (Froehlich et al., 2009). Clustering can also be used to evaluate policy changes. For example, Lathia et al. investigated the variations of clusters before and after the implementation of new user-access policy and found many stations exhibit an opposite trend after the policy change (Lathia, Ahmed, & Capra, 2012). For trip data, community detection can be employed to identify subgroups of areas that have strong intra-area connection than inter-area. It was also found to effectively reveal the spatial structures and communities of bike-sharing systems in a comparative study of five cities (Austwick, OBrien, Strano, & Viana, 2013).

Geo-visualization of the spatiotemporal patterns provides a powerful tool to comprehend the dynamics of bike sharing. For example, Corcoran et al. mapped the bike flows between regions in different time periods to study the impacts of weather conditions and calendar events on the cycling dynamics in Brisbane (Corcoran, Li, Rohde, Charles-Edwards, & Mateo-Babiano, 2014). They found that strong winds and rainfall reduce the number of trips significantly while the effect of temperature is limited and the calendar events induce subtle change in the spatial distribution of trips. Through visualizing trip chain as elliptic curves, Zhao et al. revealed significant variations between men and women in using public bikes, as well as between weekday and weekends (Zhao, Wang, & Deng, 2015). Another study by Zhang et al. examined the trip chains and transition activities of bike-sharing trips in

Zhongshan, a city of Guangdong province in China where non-motorized transport took the biggest mode share and found that most users use cycling as a single transport mode for commuting (Zhang, Brussel, Thomas, & van Maarseveen, 2018). More comprehensive visualization of bike-sharing trips can be found in (Oliveira, Sotomayor, Torchelsen, Silva, & Comba, 2016). It developed an interactive visualization tool to support exploring mobility patterns of bike sharing which can help bike-sharing companies better serve the commuters.

2.3. Determinants of bike-sharing trips

Understanding the determinants of human travels by different transportation means (e.g., metro, bus, taxi and bicycle usage) can inform urban planning and policy making (Tu et al., 2018; Zhang, Xu, Tu, & Ratti, 2018; Zhou et al., 2017). Previous studies have devoted considerable efforts into examining the usage of bike-sharing systems and its influencing factors. Demographics such as population density, median household income, and automobile ownership have been proved to impact the spatiotemporal dynamics of shared bike trips (Buck & Buehler, 2012). Many studies also demonstrated that built environment indicators such as proximity to bus and train stations, density docking stations, length of bike lanes as well as density of and proximity to points-of interests (POIs) among others are generally positively correlated with cycling demand (de Chardon, Caruso, & Thomas, 2017; Wang, Lindsey, Schoner, & Harrison, 2015; Zhang, Thomas, Brussel, & Van Maarseveen, 2017). Considering the seasonal and daily variations of bicycle usage, weather is another nonnegligible factor. El-Assi et al. reported that weather conditions (e.g., humidity, temperature, precipitation and snow) in addition to demographic and built environment characteristics have remarkable influence on the demand of shared bike trips in Toronto, Canada (El-Assi, Mahmoud, & Habib, 2017). Zhao et al. found gender also an important factor when examining the duration of shared bike trips and the formation of trip chains in Nanjing, China (Zhao et al., 2015). Their study found that women are more likely to make round trips than men, especially on weekdays. Faghih-Imani and Eluru incorporated spatial and temporal effects for modelling bicycle demand of bike sharing system in New York (Faghih-Imani & Eluru, 2016). Exogenous variables such as transport network infrastructure, POIs, and temporal attributes were incorporated in their models. In short, the above studies suggest that population density, employment density, bicycle infrastructures (i.e, lanes, bike station count, station density, etc.), transportation law (e.g., liquor licenses and Helmet), and other built environment characteristics (e.g., land use mixture) are potential factors that impact the usage of bike-sharing systems.

Most of the previous studies examined the usage of shared bikes at station level mainly due to the fact that early bike-sharing systems relied on docking stations for fleet management and service stability. The new dockless bike-sharing system, however, released this restriction which allows bike users to initiate and terminate their trips wherever they desire. Therefore, previous studies focusing on shared bike usage at station level confront challenges as trips are no longer biased towards docking stations. Recently, Shen et al. noticed this difference and modelled the impact of fleet size, built environment characteristic and weather condition on the usage of dockless bike-sharing system in Singapore (Shen et al., 2018). They found that the usage of shared bikes increased with the expansion of the fleet size though its marginal return diminishes, and weather and built environment play important roles as well. However, limited attention was paid to the spatiotemporal dynamics of bicycle usage. Considering the hour-to-hour variations, our study goes further to delineate the landscape and the pulses of cycling activities through eigendecomposition, thus providing a comprehensive picture of the usage patterns of shared bikes in a condensed city.

3. Research design

3.1. Extract origin-destination trips from the bike-sharing dataset

Singapore is a city-state with a total area of 721.5 km^2 and a population of 5.6 million as of 2016. It is one of the most densely populated and urbanized areas in the world. The city possesses an integrated public transport system with a mode share of 67% during peak hours. Among different public transport modes, buses take up 48% of the average daily ridership, as compared to 38% for mass rapid transit (MRT), 12% for taxis, and 2% for light rail transit (LRT). Dockless bike-sharing programs entered Singapore in February 2017 and expanded rapidly thereafter. By the end of October 2017, one of the largest operators in Singapore has deployed more than fifty thousand bikes in the island city.

The GPS dataset[1] used in this study was collected from one of the largest dockless bike-sharing operators in Singapore from July 1st to October 31st, 2017. It tracks for each bike a unique 9-digit ID and the real-time location at an average frequency of 55 s when the bike is not occupied. In other words, the locations of bikes are not reported in this dataset when they are rented by users. By organizing the geolocations of each bike in chronological order, we reconstruct GPS trajectories of all the bikes, and perform a trajectory segmentation to derive OD trips.

After sorting the GPS records of each bike chronologically, we first merge consecutive records with the same coordinates (lat/lng) and mark the start and end time of the bike's stay at such locations. This results in a location sequence $\{X_1, X_2, \dots, X_n\}$, where $X_i = (l_i, t_i)$ denotes a tuple of observation location and the timestamp. We then identify oscillation sequences such as A_0-A_1-A_0 and A_0-A_1-A_0-A_1-A_0, where A_0 and A_1 refer to the consecutive location records in sequence $\{X_1, X_2, \dots, X_n\}$. This step is essential because it is unlikely that one can ride a bike back to a location that is exactly the same as its previous location even if it is a round trip. In other words, such oscillation sequences are likely to be caused by GPS drifting. To tackle this issue, the medoid of each oscillation sequence is used to denote its representative location (i.e., A_0 for sequence A_0-A_1-A_0), and we replace the corresponding observations in $\{X_1, X_2, \dots, X_n\}$ with those medoids to form a new sequence $\{Y_1, Y_2, \dots, Y_n\}$. After removing the oscillation sequences, it is still possible that some of the short-range displacements in $\{Y_1, Y_2, \dots, Y_n\}$ are caused by the imprecision of GPS positioning. According to the statistics of a recent household interview travel survey (HITS) in Singapore, almost all trips of the participants are longer than 150 m, with exceptions of only six cycling trips which have the same origin and destination (Shen et al., 2018). Therefore, to mitigate the issue of location uncertainty, we iteratively merge two consecutive locations in $\{Y_1, Y_2, \dots, Y_n\}$ with distance smaller than 150 m and mark their locations using the mean center. Finally, OD pairs are extracted from the processed sequences and trips with a speed higher than 30 km/h are filtered as invalid movements that could be caused by the redistribution of bikes.

Fig. 1 shows the hourly number of trips averaged by day of week. Bicycle usages from Monday to Friday show similar temporal patterns. Two peaks are observed around 8:00–9:00 and 19:00–20:00, and a higher number of trips is made by bicycle users during evening hours. Cycling activities on weekends possess a different temporal profile. Although the average travel demand in the early morning (08:00–09:00) is compatible to that of weekdays, bicycle usage on weekends reaches its first peak around noon time. Similar to weekdays, there is a higher demand of shared bikes after 18:00. In general, bicycle usages exhibit recurrent patterns on both weekdays and weekends. From a spatial point of view, as shown in Fig. 2, cycling activities are concentrated in particular areas of Singapore. The spatial distributions

[1] See a visualization for more information about the dataset: https://www.youtube.com/watch?v=_yfiuV4j9Jw

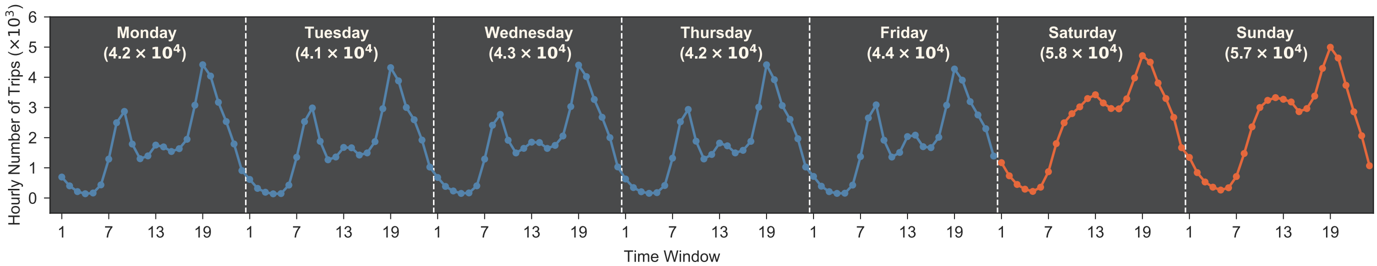

Fig. 1. Hourly number of trips averaged by day of week.

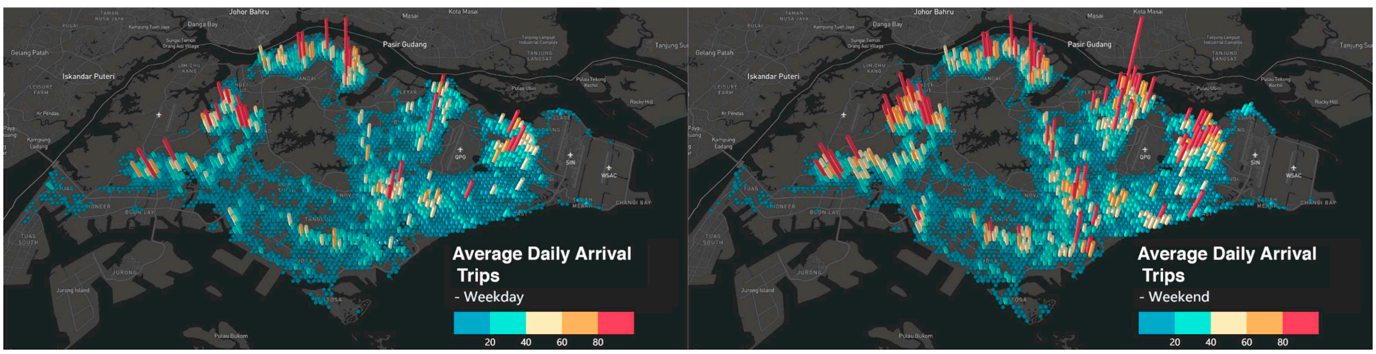

Fig. 2. Spatial distribution of arrival trips on weekdays and weekends.

are similar between weekdays and weekends, while slight differences are observed in certain areas. For example, there is a higher demand for shared bikes on weekends along the east coast, an outdoor attraction for tourists and cyclists.

3.2. Analyze the spatiotemporal patterns of cycling activities through eigendecomposition

This research introduces an eigendecomposition approach to analyze the spatiotemporal patterns of cycling activities in Singapore. The technique was employed by previous researchers to uncover the rhythms of mobile phone usage (Reades, Calabrese, & Ratti, 2009) and human mobility patterns (Eagle & Pentland, 2009; Gong, Lin, & Duan, 2017). Eigendecomposition can be used to obtain the principal components (PCs) of a dataset that best align with its inherent variation. The resultant PCs, ranked by the fraction of the variance explained, indicate the underlying structure of the dataset. While the corresponding coefficients associated with a particular entity (e.g., temporal usage pattern of bikes at a location) demonstrate its deviation from the norm (i.e., average pulse of the city). Thus, the eigendecomposition can be employed to answer our first research question — how do the temporal patterns of bicycle usage at different places resemble or deviate from the base mode of the city?

Given that the temporal patterns of travel demand might be different at trip origins and destinations as well as on different types of days, this research performs the eigendecomposition under four combinations: (1) arrival trips on weekdays, (2) departure trips on weekdays, (3) arrival trips on weekends, and (4) departure trips on weekends. To capture the temporal signatures of travel demand across the island, we divide Singapore into 500 × 500 m grid and match the extracted OD pairs to each square. Note that among the 3,581 squares that are generated, cycling activities are only observed in 1,095 squares. It is also observed that bicycle trips tend to be concentrated in particular areas of the city. Given the low-level usage of bikes in particular areas, this study limits the analysis to the top 50% of the active squares. These 545 squares represent 80% of the total demand and each has an average daily trips of more than 53.

Using departure trips on weekdays as an example, for each square, we compute the hourly number of trips averaged across all weekdays and normalize them using the average daily total of this square. This results into a vector[2] $\Psi_i = \{r_{i,\ 1}, r_{i,\ 2}, \ldots, r_{i,\ 24}\}$ where $r_{i,\ j}$ refers to the hourly percentage of trips originated from square i during time window j. Note that:

$$\sum_{j=1}^{24} r_{i,j} = 1 \tag{1}$$

By averaging Ψ_i across all the squares, we obtain the base mode of cycling activities in the city:

$$u = \frac{1}{N}\sum_{i=1}^{N}\Psi_i \tag{2}$$

where N refers to the total number of squares (545 in this study). A matrix M of size $N \times 24$ is then constructed with each row being $\Phi_i = \Psi_i - u$, which describes the deviation of a square's temporal signature from the base mode:

$$M = \begin{pmatrix} r'_{1,1} & r'_{1,2} & \cdots & r'_{1,24} \\ r'_{2,1} & r'_{2,2} & \cdots & r'_{2,24} \\ \vdots & \vdots & \ddots & \vdots \\ r'_{n,1} & r'_{n,2} & \cdots & r'_{n,24} \end{pmatrix} \tag{3}$$

The covariance matrix C can then be calculated as:

$$C = \frac{1}{N}\sum_{i=1}^{N}\Phi_i^T\Phi_i = \frac{1}{N}M^TM \tag{4}$$

We then calculate the eigenvectors $v_1, v_2, \ldots, v_{24}$ and the associated eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_{24}$ of C, with λ_j ranked in descending order. The set of eigenvectors of covariance matrix C — which are orthogonal to each other — are the PCs of matrix M, and the associated eigenvalues denote the variance explained by each PC. The transformed dataset A of size $N \times 24$ under the new coordinate system can be found as:

[2] A vector in this article corresponds to a row vector unless otherwise specified.

$$A = MV^{-1} \tag{5}$$

where

$$V = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_{24} \end{pmatrix} \tag{6}$$

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,24} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,24} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \cdots & a_{n,24} \end{pmatrix} \tag{7}$$

In matrix A, $a_{i,\,j}$ refers to the coefficient of the j^{th} PC for the i^{th} square and thus each row contains the loadings of PCs for one entity (square). Given a square, its coefficient of a PC indicates to what extent the square's temporal patterns deviate from the base mode of the city. Note that the original behaviour of a square can be reconstructed as follows:

$$\Psi_i = u + A_i V \tag{8}$$

where A_i refers to i^{th} row vector of matrix A.

We then seek to unravel the overall structure of the dataset by interpreting the significant few PCs and understand the temporal characteristics of squares by examining their coefficients of these PCs. How many PCs can adequately explain the original dataset is an important but controversial problem in the realm of principal component analysis. Here we adopt the empirical rules proposed in (Jolliffe, 2010): (1) the first few PCs that account for more than 70% of the variance of the total dataset; (2) the first few PCs whose eigenvalues are more than the 0.7 times the average of eigenvalues, and (3) PCs that are to the left of the elbow points in the scree plot.

3.3. Derive built environment indicators

Built environment is considered to have strong influence on human travel patterns and their mode choice. In this research, we construct several key built environment indicators based on information of land use and transportation infrastructure to investigate their associations with shared bike usages. In particular, seven indicators, namely, floor-area ratio (FAR) of residential building, FAR of commercial building, land use mixture, network distance to MRT, number of bus stops, number of road intersections, and length of cycling path, are derived.

Land use density and diversity which reflect urban functions are often evaluated in transportation and behavioral research. Here, the floor-area ratio (FAR) is used to denote land use densities. Both residential and commercial densities are derived from a building database from the Singapore Land Transport Authority (LTA). The diversity or land use mixture is measured based on 40,782 points-of-interest (POIs) collected by the Google Place API. After reclassifying the POIs into seven categories, as shown in Table 1, the Shannon entropy of each square is calculated to reflect its land use mixture:

$$H = -\sum_{i=1}^{n} (p_i) * log_n(p_i) \tag{9}$$

where p_i denotes the percentage of POIs belonging to the i^{th} category, and n is the total number of categories.

Transportation infrastructure also plays an important role in shaping individual mode choice. It is assumed that dockless bike-sharing would strengthen the first- or last-mile connection to public transit stations. To validate this hypothesis, for each square, its distance to the nearest MRT station as well as the number of bus stops are computed. The distance to MRT is calculated as the network distance of the shortest route from the centroid of the square to its nearest MRT station. Note that Singapore government has built dedicated cycling paths to promote active mobility. The total length of cycling path in each square is measured to examine the effectiveness of these cycling infrastructures. In addition, the total number of road intersections is calculated to reflect the road network density, which can also be thought as a surrogate for street block size.

4. Results

4.1. Temporal signatures of bicycle usage

In this section, we first examine the space-time structures of bicycle usage derived from the eigendecomposition. Table 2 presents, for each type of trip, the total variance of the temporal signatures (at different squares) and the percentage of variance explained by the top few PCs. According to the results, the four types of trips possess quite different structures. Trips on weekdays — no matter arrival or departure — exhibit greater variance than their counterpart on weekends. The rhythms of cycling activities on weekdays vary considerably from place to place while it is more universal on weekends. By fixing the type of day, we find that the variance of arrival trips is always higher than that of departure trips, indicating a higher diversity of temporal patterns at trip destinations. As trip destinations are tight to specific activity purposes, places with different urban functions tend to produce different bicycle usage patterns, resulting in a higher variance of the temporal patterns.

For both departure and arrival trips on weekdays, their 1^{st} PCs account for a very large proportion of the total variance, and the top two PCs, in combination, explain about 90% of the total variance. That means the temporal patterns of bicycle usage on weekdays tend to vary along certain directions (i.e., during certain time periods). Trips on weekends, however, have less dominating 1^{st} PCs, and it requires four PCs to explain 90% of the total variance. This suggests that bicycle usages at different places on weekends are more scattered, or random, in the high dimensional temporal space. In short, the eigendecomposition results illustrate a more dynamic yet rhythmic usage of shared bikes on weekdays, and a more static yet slightly random structure on weekends.

Given a certain type of trip, the top few PCs and their characteristics reveal important information about the data structure. By examining

Table 1
Categorization of POIs from Google Place API.

	Category	Examples
1	Company and small business	Accounting services, banks, doctor, dentist, travel agency, laundry
2	Government, organizations, institutions	Church, city hall, embassy, museum, police, post office, university, school
3	Entertainments	Art gallery, bar, beauty salon, casino, gym, hair care, movie theater, spa
4	Hotels	Lodging, hotels
5	Retail	Bakery, book store, department store, gas station, supermarket, liquor store, shopping mall
6	Restaurants	Cafe, food, restaurant
7	Transportation	Airport, bus stations, subway stations, taxi stand, train stations

Table 2
Variance explained by the principal components ($\times 10^{-8}$).

Trip type	Total variance	Average variance	Variance explained by			
			$1^{st}PC$	$2^{nd}PC$	$3^{rd}PC$	$4^{th}PC$
Weekday arrival trips	21.8	0.907	18.7 (86%)	1.45 (7%)	0.615 (3%)	0.576 (3%)
Weekday departure trips	13.4	0.560	9.16 (68%)	2.89 (21%)	0.575 (4%)	0.407 (3%)
Weekend arrival trips	3.07	0.128	1.33 (43%)	0.807 (26%)	0.453 (15%)	0.197 (6%)
Weekend departure trips	2.69	0.112	1.45 (54%)	0.597 (22%)	0.232 (9%)	0.143 (5%)

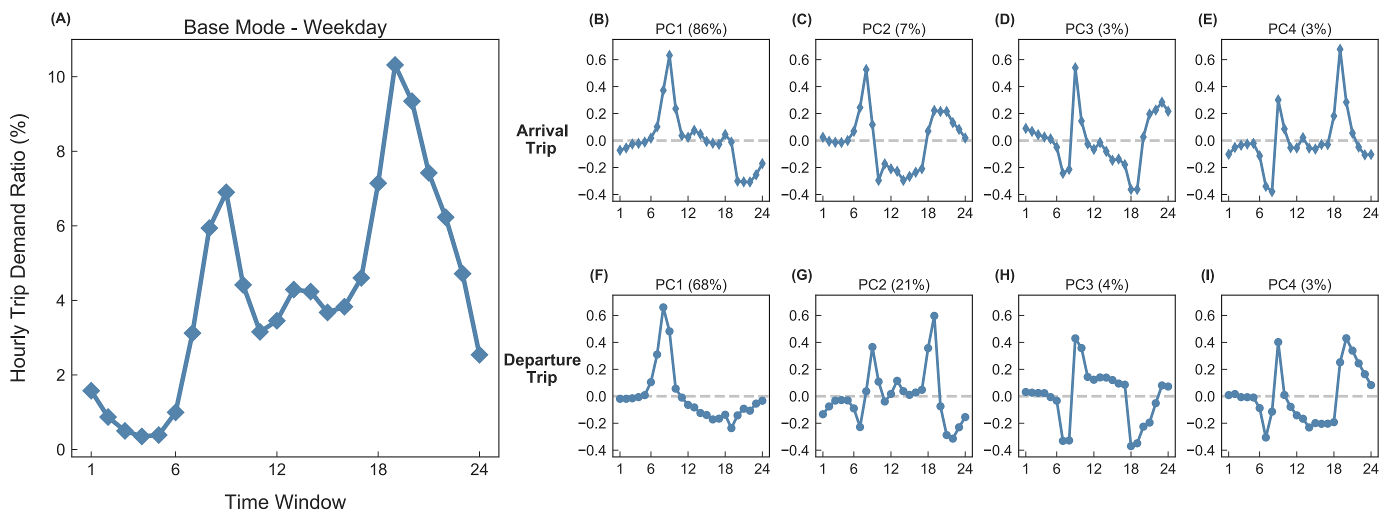

Fig. 3. Results of eigendecomposition — weekday.

the 1^{st} PC of arrival trips on weekdays (Fig. 3B), we find a temporal pattern that peaks in the early morning. The 1^{st} PC of departure trips on weekdays — which explains a lower but still significant amount of total variance (68%) — shows a similar peak (Fig. 3F). That means cycling activeness in the morning differs from place to place in Singapore while it is less distinguishable during other periods. Slight differences, however, are observed from these two 1^{st} PCs. Specifically, the 1^{st} PC of arrival trips suggests that if a square attracts more trips during 6:00–9:00, it is less likely that cyclists will ride to this place after 19:00 (Fig. 3B). On the other hand, if more trips originate from a place during 6:00–9:00, then fewer cyclists will start their trips from this place thereafter (Fig. 3F). Note that the 2^{nd} PC of departure trips — which explains a substantial amount of the total variance (21%) — exhibits notable transitions in the early morning and late afternoon (Fig. 3G). These transitions suggest that at some places, trip generation is more active from 08:00 to 09:00 and from 17:00 to 19:00 while at other places, it is more active from 6:00 to 7:00 and in the evening. Here we don't elaborate the characteristics of other PCs since they explain a very limited proportion of the total variance.

Trips on weekends, as shown in Fig. 4, have less dominant 1^{st} PCs. But similar to weekdays, these 1^{st} PCs exhibit notable peaks during 07:00–09:00, indicating a large spatial variation of cycling activities in the morning (Fig. 4B and F). The 2^{nd} PCs explain 26% and 22% of the total variance for arrival and departure trips, respectively. These 2^{nd} PCs suggest a variation of travel patterns between daytime and other periods. In other words, if more people start their trips at a place during 09:00–16:00, then less people will ride from here in the early morning and in the evening (Fig. 4G). Such a variation also applies at trip destinations (Fig. 4C).

For a given trip category, since the top few PCs can explain a significant proportion of the total variance, the temporal characteristics of cycling activities in any square can be mainly described by the linear combination of the base mode (u) and these PCs (V), weighted by the corresponding coefficients (A_i). For example, Fig. 5A shows the joint distribution of the coefficients for the top two PCs for arrival trips across all squares on weekdays. Four locations — which intersect with the Woodlands HDB[3] Blocks, Woodlands MRT Stn, City Hall MRT Stn, and East Coast Park, respectively — are chosen to demonstrate how their temporal signatures can be effectively reconstructed (Fig. 5B–E). City Hall MRT Station is located in the CBD area of Singapore and surrounded by hotels, commercial centres, museums and St. Andrew Cathedral while, differently, Woodland MRT Station is located up to the north border of Singapore surrounded by numerous public housing blocks. Woodland HDB blocks, by its name, are public housing blocks in the north region of Singapore and this square is right next to Woodland MRT Station. East Coast Park is a seaside park with various entertainment facilities including a cycling path. The exact locations of the four places can be found in Appendix A.

The first square with Woodland MRT Stn has positive coefficients for both PC1 and PC2. These positive values indicate a higher travel demand in the early morning as compared to the base mode of the city (Fig. 3A). Thus, the actual bicycle usage at this square exhibits two peaks on weekdays, with the morning peak slightly higher than the evening one (Fig. 5B). The square in Woodlands HDB Blocks has a negative coefficient for PC1, which signifies a lower level of returning trips in the morning (Fig. 5C). Both City Hall MRT Stn and East Coast Park have negative coefficients for PC1 and PC2. The difference is that the PC1 coefficient for City Hall MRT Stn is close to zero. The dominant role of PC2 results into a temporal signature where larger ridership is

[3] HDB, which is short for Housing Development Board, is a type of residential housing property that is publicly governed and developed in Singapore. The HDB flats were built primarily to provide affordable housing.

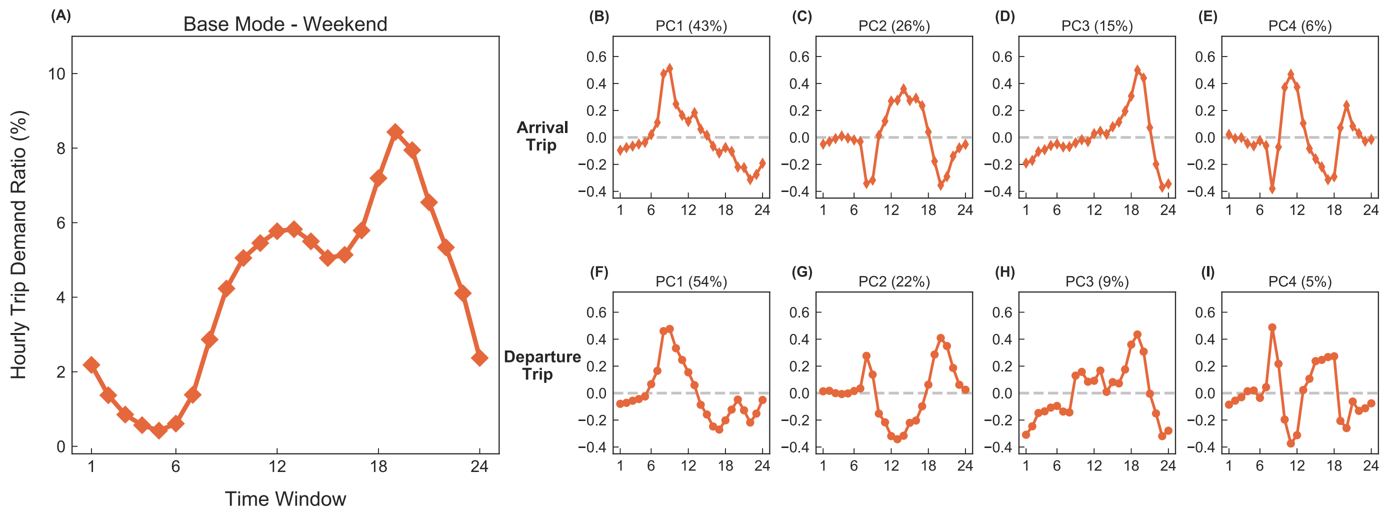

Fig. 4. Results of eigendecomposition — weekend.

observed during the daytime (Fig. 5D). Compared to City Hall MRT Stn, the square in East Coast Park has negative coefficients that are compatible between PC1 and PC2, which indicates an even lower demand in the early morning but an elevation of cycling activities in the evening (Fig. 5E). The results shown in Fig. 5 suggest that bicycle usage patterns at different places in Singapore can be well described by the first few PCs and the corresponding coefficients. Note that we can also reconstruct the main signals of cycling activities for squares when they serve as trip origins and/or on weekends. These examples can be found in Appendix A.

4.2. Association between temporal signatures and built environment characteristics

Previous studies have been conducted to examine the relationship between cycling activities and built environment characteristics (Buck & Buehler, 2012; Buehler, 2012; Mateo-Babiano, Bean, Corcoran, & Pojani, 2016; Rixey, 2013; Wang et al., 2015). These studies — with their focus on traditional station-based bike-sharing systems — have suggested a close relationship between the two. This section investigates the relationship between the temporal signatures derived from eigendecomposition and the key built environment indicators. Table 3 shows the summary statistics of the seven indicators for the active squares (545 in total), along with the statistics for all squares with cycling activities as a reference (1,095 in total). In general, the active squares tend to have better accessibility to public transit stations, higher residential and commercial densities, more diverse land uses, and better deployment of road network and cycling paths.

For each trip type, as described previously, the first one or two PCs are able to explain a significant proportion of the total variance. The coefficients of these PCs can thus be used to describe the temporal patterns of bicycle usage at different urban locations. For weekday

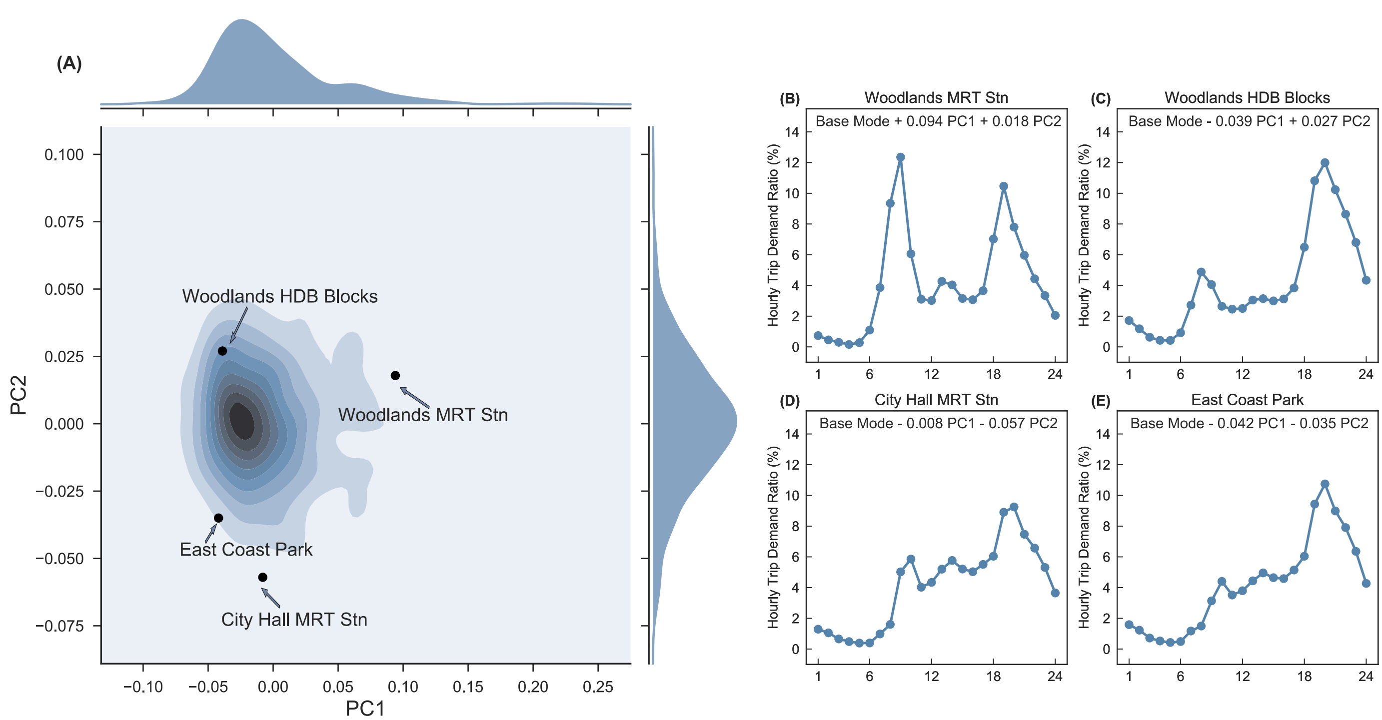

Fig. 5. (A) Joint distribution of PC1 and PC2 coefficients of the squares (weekday arrival trips); (B-E) Temporal patterns of the four locations reconstructed from these two PCs.

Table 3
Statistics of built-environment characteristics.

	Squares with cycling activities		Top 50% Active squares	
	Mean	Standard deviation	Mean	Standard deviation
FAR of residential building	0.58	0.57	0.86	0.92
FAR of commercial building	0.10	0.25	0.12	0.29
Land use mixture	0.55	0.23	0.62	0.18
Network distance to MRT [km]	1.84	1.36	1.41	0.9
Number of bus stops	3.56	2.49	4.63	2.34
Number of road intersections	18.68	13.04	24.09	12
Length of cycling path [m]	48.83	190.97	84.73	236.86

arrival trips, we examine the relationship between the coefficients of the 1^{st} PC and the associated built environment indicators (Fig. 6). Here only the 1^{st} PC is selected because it accounts for 86% of the total variance. In other words, the squares show very little difference along other eigenvectors (Appendix B). According to the results, two indicators — namely residential density and land use mixture — have a negative although not strong correlation with PC1 coefficients (Fig. 6A and C). This indicates that locations with a higher public housing density or mixed land use tend to attract fewer trips in the morning while more in the evening. A very weak relationship, if any, is found between the PC1 coefficient of a square and its network distance to the nearest MRT station. However, to study whether MRT stations have a potential effect in absorbing bicycle trips, we further produce a box plot, showing the distribution of PC1 coefficients of the squares with MRT stations against others (Fig. 6H). It is observed that most squares with MRT stations have positive PC1 coefficients, while most of others hold negative values. Compared to the base mode of the city, MRT stations attract more trips during morning rush hours while fewer after 19:00. This indicates that shared bikes in Singapore serve as a potential feeder to the MRT stations, facilitating the first-mile trips in the morning.

For weekday departure trips, instead of using only the 1^{st} PC, the 2^{nd} PC is also included in the correlation analysis due to the 21% of the total variance it has explained. Specifically, we organize the squares based on the combination of PC1 and PC2 coefficients, and compute the mean value of the built environment indicators (Fig. 7). We also examine the distributions of coefficients for squares with and without MRT stations. In contrast to the fact that MRT stations attract more trips during morning rush hours (Fig. 6H), they produce fewer trips in the early morning, as most of the MRT squares hold a negative PC1 coefficient (Fig. 7A). It is likely thatin Singapore, shared bikes are more of a "first-mile" solution than the "last-mille" facilitator. Interestingly, when looking at the distribution of PC2 coefficients, it is mostly positive for locations with MRT stations while negative for others (Fig. 7B). On the one hand, it suggests that more trips are initiated from MRT stations around the end of the morning rush hours (i.e., 8:00–9:00) rather than at the beginning (i.e., 6:00–7:00). On the other hand, more trips tend to start from MRT stations during afternoon rush hours (i.e., 17:00–19:00) than in the evening. Therefore, we may deduce that shared bikes do serve as a "last-mile" solution although to a limited extent.

High residential densities are mainly associated with positive PC1 and negative PC2 coefficients (Fig. 7C), indicating that in the morning, residential blocks are the major generators of cycling trips. Squares with higher commercial densities are associated with negative PC1 and positive PC2 coefficients (Fig. 7D), suggesting a lack of demand from commercial areas in the early morning. No clear relationships,

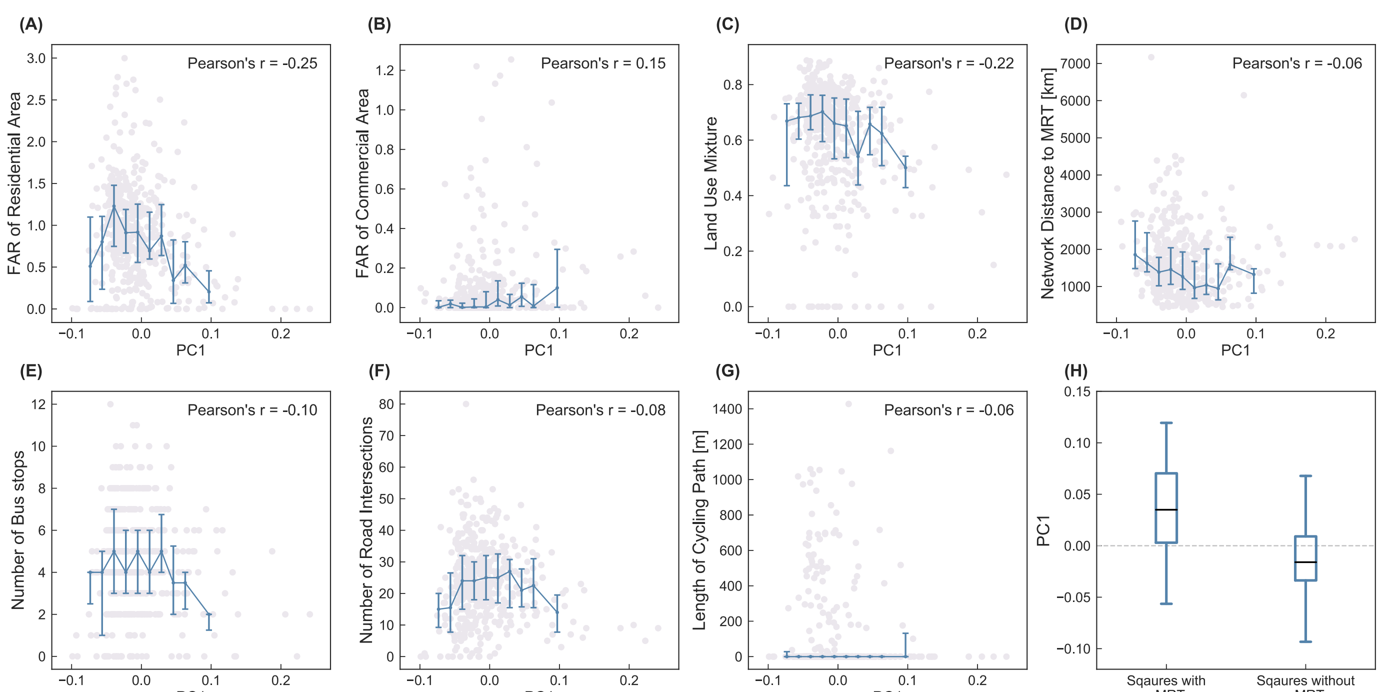

Fig. 6. (A–G) The relationship between PC1 coefficients and built environment indicators — weekday arrival trips; (H) Distribution of PC1 coefficients for squares with and without MRT stations.

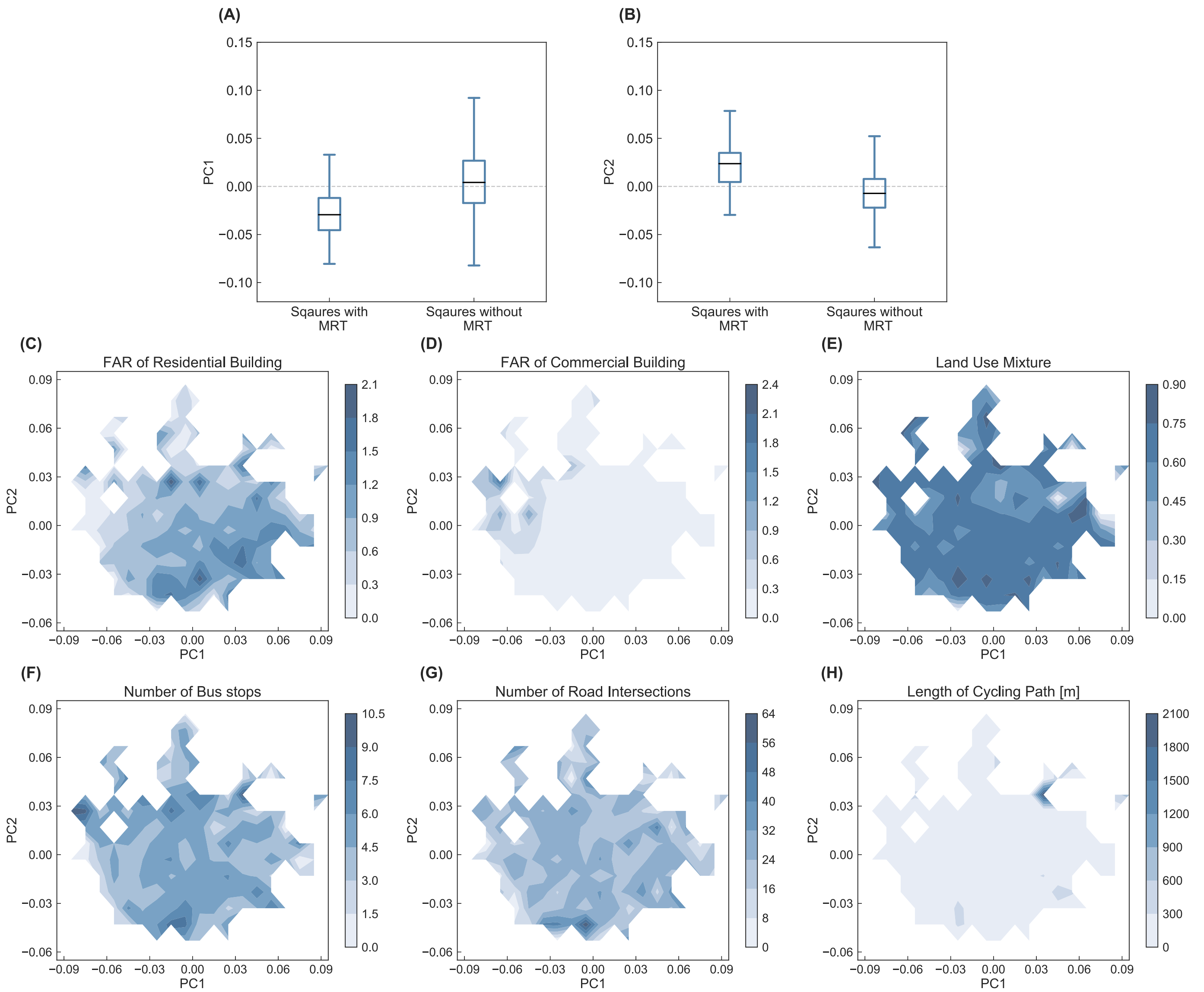

Fig. 7. (A–B) Distribution of PC1 and PC2 coefficients for squares with and without MRT stations — weekday departure trips; (C-H) Mean value of built environment indicators for squares with different temporal patterns.

however, are observed between the squares' temporal signatures and other built environment indicators (Fig. 7E–H).

Figs. 6 and 7 suggest that the temporal signatures of cycling activities on weekdays exhibit a structural variation that — to some extent — aligns with the pulses of morning commuting activities in Singapore. In the morning, the attractiveness of MRT stations increases, which is partly contributed by the areas nearby, notably public housing districts. On the other hand, although cycling demand in Singapore is higher in the evening, trip purposes during off hours are more diverse. Thus, the temporal signatures are less coupled with specific location characteristics.

For weekend arrival trips, areas with negative PC1 but positive PC2 coefficients tend to have high commercial densities (Fig. 8D). The result suggests that areas with active commercial development are associated with lower attractiveness for cyclists in the early morning, but increased popularity later on (i.e., after 10:00). In contrast, areas with positive PC1 and PC2 coefficients tend to have more bus stops in general (Fig. 8F), suggesting more bicycle trips absorbed by these areas from early morning till late afternoon, but not in the evening. We should also be reminded that some areas with compatible bus stop deployments exhibit very different temporal signatures, which indicates a more complicated relationship between the amount of bus stops and the corresponding temporal signatures. The number of road intersections in a square is positively correlated with PC2 coefficient (Fig. 8G), suggesting that urban locations with a dense road network tend to attract more cyclists during the daytime.[4] Other built environment indicators, such as residential density, land use mixture, and length of cycling path, play less a role in shaping the temporal signatures of cycling activities as no obvious correlations are observed.

For weekend departure trips, most of the MRT squares have negative PC1 and PC2 coefficients (Fig. 9A and B), suggesting that MRT stations — compared to the base mode of the city — produce fewer trips in the morning. It is also observed that areas with higher PC1 coefficients tend to have higher residential densities (Fig. 9C), indicating that for dense housing areas, more trips are generated in the early morning particularly during 08:00–10:00. Areas with negative PC1 and PC2 coefficients have higher commercial densities (Fig. 9D) and more bus stops deployed (Fig. 9F). Compared to the absorbing effect from early

[4] Readers could refer to Appendix C for correlations between built environment indicators and each of the two PCs.

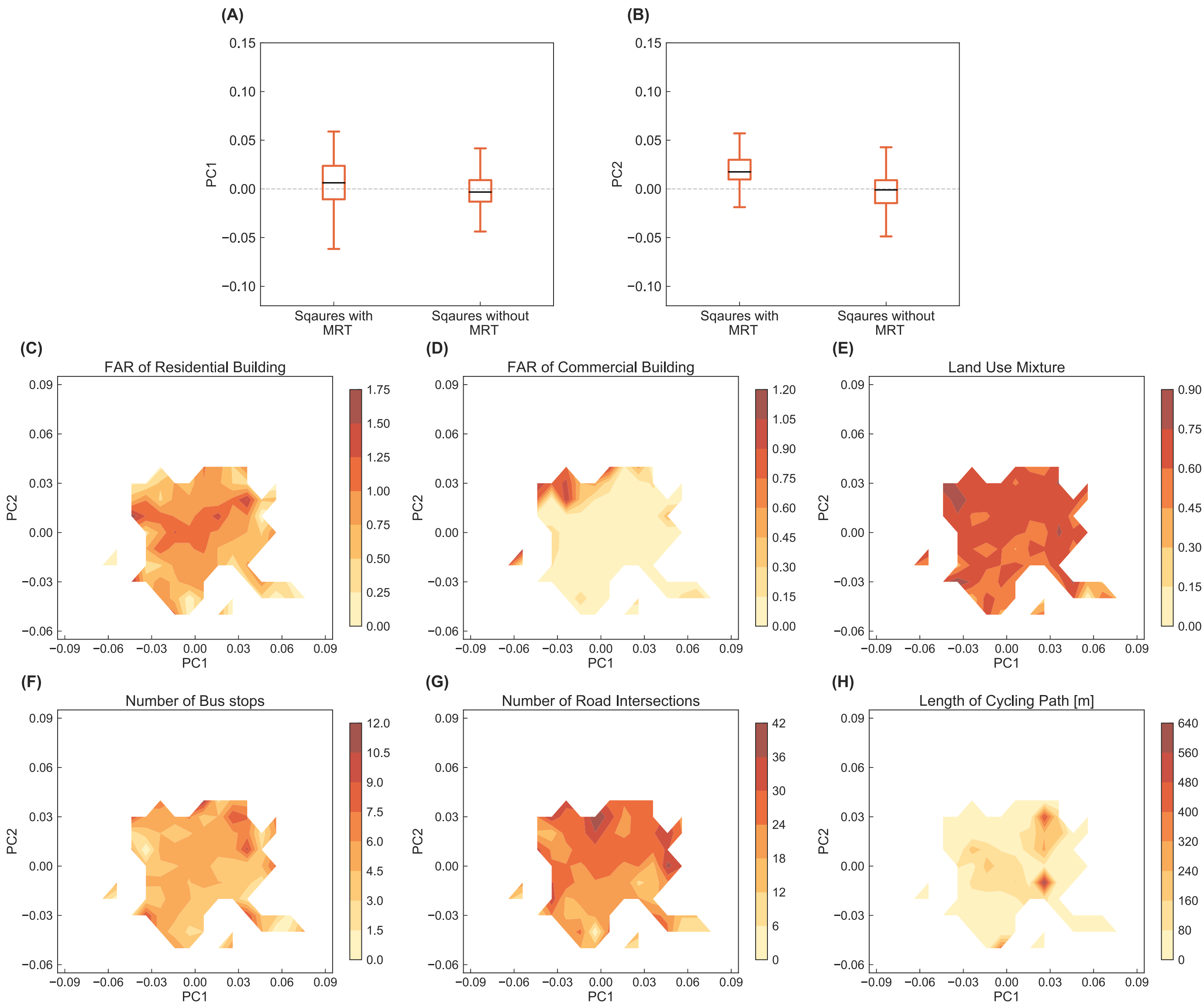

Fig. 8. (A–B) Distribution of PC1 and PC2 coefficients for squares with and without MRT stations — weekend arrival trips; (C-H) Mean value of built environment indicators for squares with different temporal patterns.

morning till late afternoon (Fig. 8D and F), these areas produce more bicycle trips only in the afternoon and during the night. The comparison between arrival and departure trips reveals the rhythms and asymmetry of cycling activities at these locations.

4.3. Spatial distribution of squares with distinctive temporal patterns

The eigendecomposition and correlation analysis have highlighted the temporal structures of cycling activities in Singapore and their relationship with the underlying built environment. To complement our findings, this section further discusses areas with distinctive temporal usage patterns and their geographic distributions.

On weekdays, the temporal patterns of cycling demand at trip destinations can be dichotomized into two groups based on the values of PC1 coefficient. The geographic distributions of these two groups are visualized in Fig. 10A, overlaid with stations and routes of the MRT system. Locations with positive PC1 coefficients, as described previously, tend to attract more bicycle trips in the early morning. Many of these locations, as shown in Fig. 10A, refer to squares with MRT stations or the adjacent ones. The finding is in line with the discussion in Section 4.2 that during morning rush hours, MRT stations play a more vital role in absorbing trips than other locations, highlighting its potential contribution to facilitating the “first-mile” of morning travels. Apart from this co-location pattern, we also find a cluster of squares with higher morning attractiveness in the north region of Singapore, which is part of the Woodlands-Sembawang-Yishun community. These squares could serve as the final destinations of cyclists on weekday mornings. Right next to the north border of Singapore and distant away from the city center, this area — as we conjecture — is relatively more self-sufficient where citizens live and work. Such a job housing balance may stimulate many intra-region cycling trips.

Regarding bicycle usage at trip origins (Fig. 10B), squares that generate more trips in the morning (PC1 coefficient > 0) are generally residential blocks that are relatively close to the MRT stations.

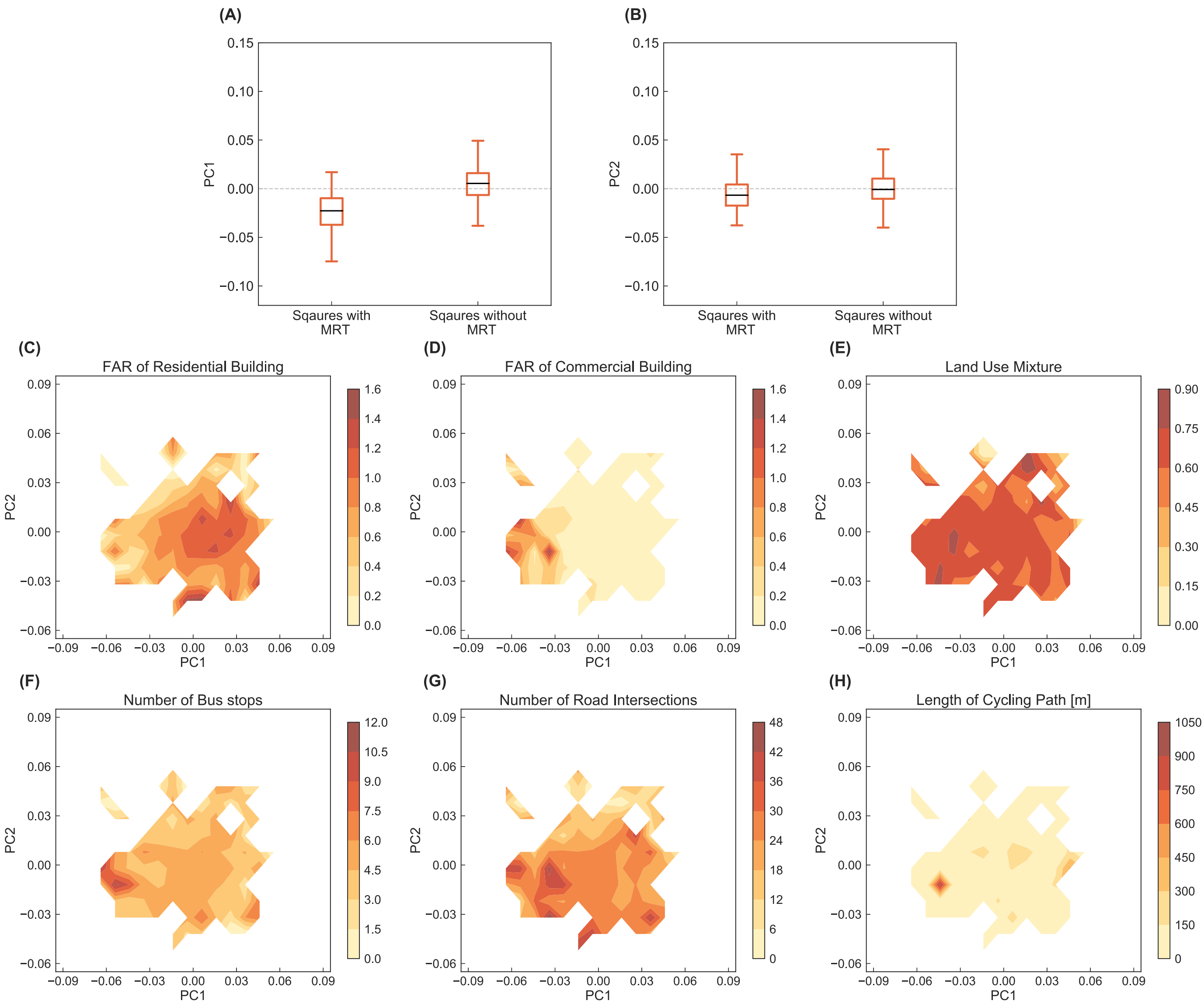

Fig. 9. (A–B) Distribution of PC1 and PC2 coefficients for squares with and without MRT stations — weekend departure trips; (C-H) Mean value of built environment indicators for squares with different temporal patterns.

However, some of them are more active during 8:00–9:00 in the morning and 18:00–19: 00 in the evening (red squares with PC2 coefficient > 0), while some others more active during 6:00–7:00 and in the evening (blue squares with PC2 coefficient < 0). We are unable to uncover the driving forces that lead to these differences based on the data we have used in this research. Incorporating other socio-demographic information — such as census and household interview travel survey — might help further explain the observed patterns. Another finding on weekdays is that the MRT stations and the CBD area generate limited bicycle trips in the early morning (Fig. 10C). On the one hand, it suggests the lack of "last-mile" trips from MRT stations as compared to the "first-mile" ones to the stations. On the other hand, it highlights the non-residential function of the CBD, where massive employment opportunities are offered by corporations and government agencies.

Referring back to the discussion of weekend arrival trips (Fig. 8A), we find that part of the MRT stations — the ones with positive PC1 coefficients — attract more trips in the morning, while the rest tends to receive more trips in the evening. As shown in Fig. 10D, MRT stations in residential areas mostly possess positive PC1 coefficients, indicating that residents ride to MRT stations more in the morning and afternoon as they engage in weekend activities and ride less to MRT stations in the evening. On the contrary, most of the MRT stations in the CBD area have negative PC1 coefficients. This can be caused by the lack of demand on weekend mornings, followed by an increased attractiveness in the evening as citizens ride to MRT stations after finishing weekend activities. Besides the MRT squares, we further visualize all the squares with negative PC1 but positive PC2 coefficient in Fig. 10E. These squares, as discussed in Section 4.2, are associated with high commercial densities. Through Fig. 8D and E, one may observe that high commercial density areas, the CBD area, and the commercial centers around MRT stations, are more attractive on weekend afternoons and evenings.

For weekend departure trips, we visualize the spatial distribution of

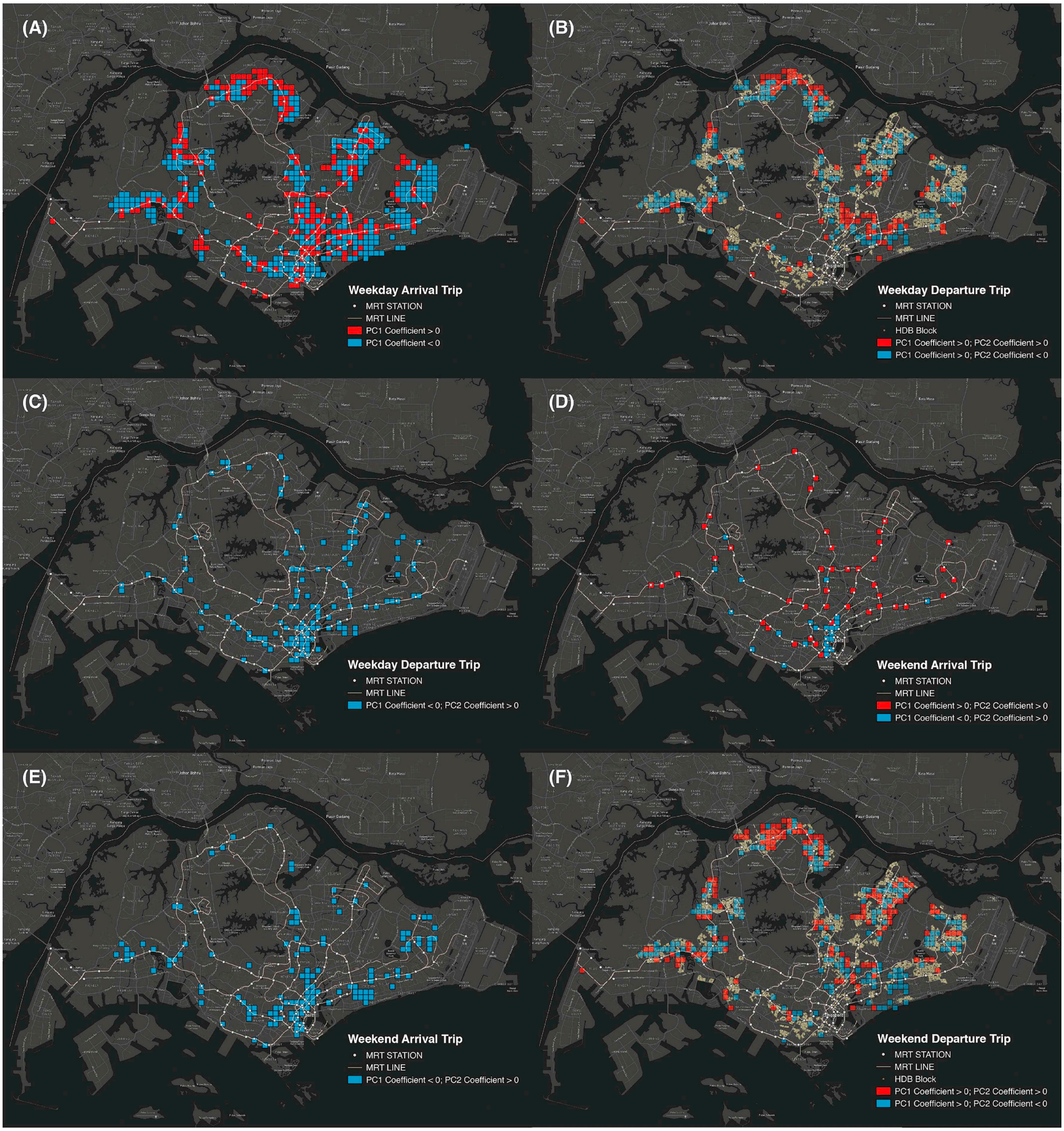

Fig. 10. Spatial distribution of squares with distinctive temporal patterns.

squares with positive PC1 coefficients (Fig. 10F). These locations serve as active trip generators in the morning and they match relatively well with the residential areas in Singapore. However, some of these locations exhibit a rush-hour surge in trip generation (red squares with PC2 coefficient > 0) while the others produce more trips during the daytime (blue squares with PC2 coefficient < 0). Although the reasons remain unclear, it is possible that such a difference in the temporal signatures is related to particular types of human activities. For instance, areas where cyclists perform more routine tasks (e.g., business and work related activities) might rely more on shared bikes during rush hours. At other places, where trips are more diverse and induced more by recreational activities, the rush-hour surge might be smoothed out by the daytime activeness.

5. Conclusions and discussions

Dockless bike-sharing systems are undergoing rapid expansions in Asian cities and worldwide. This will provide new opportunities yet challenges to city operations, affecting how transport systems and road infrastructures are designed and used. To date, limited research efforts have been devoted to uncovering the space-time structures of ridership from dockless bike-sharing systems. To fill this research gap, we analyze a four-month GPS dataset collected from a major bike-sharing operator in Singapore. Based on millions of cycling trips extracted from the dataset, we depict the temporal variations of bicycle usages at various locations in the city. An eigendecomposition approach is hen used to uncover the hidden structures of these temporal patterns.

The results illustrate a multifaceted view of shared bike usages in Singapore. On weekdays, cycling activities possess a variety of temporal profiles at both trip origins and destinations, highlighting substantial variations of bicycle usage across urban locations. Strikingly, a significant proportion of these variations (68% to 86%) is explained by the first principal components (PCs) of the eigendecomposition. The characteristics of these PCs suggest that cycling activeness in the early morning play a key role in distinguishing bicycle usage patterns at different places. On weekends, for both departure and arrival trips, the overall variation is smaller than their counterpart on weekdays, suggesting a more uniform distribution of temporal signatures across the urban landscape. However, the eigendecomposition for weekends produces less dominant 1^{st} PCs, and it requires four PCs to explain more than 90% of the total variance. That means in Singapore, cycling activities possess a more dynamic yet rhythmic space-time structure on weekdays, while a more static yet slightly random structure on weekends.

The eigendecomposition approach can effectively describe the temporal signatures of cycling activities at various locations based on their coefficients of the first few (one or two) PCs. These coefficients are then correlated with key built environment indicators to understand the relationship between bicycle usage and urban space configurations. Compared to the base mode of the city, locations with a higher residential density or land use mix tend to attract fewer trips on weekday mornings while more in the evening. These residential blocks serve as active trip generators in the morning, during which a lack of travel demand is also observed from commercial areas. Other built environment indicators, such as length of cycling path in a square, is not correlated with the temporal signatures. This is partly because a considerable proportion of trips takes place along sidewalks and footpaths, and dedicated cycling lanes only cover particular areas of the island city.

Another important finding on weekdays is that MRT stations have a notable absorbing effect during morning rush hours, while they produce fewer trips during the same periods. This suggests that shared bikes in Singapore are more of a “first-mile” facilitator than the “last-time” solution. However, more in-depth analysis reveals that at MRT stations, more trips are initiated around the end of the morning rush hours rather than at the beginning, and more trips are produced during afternoon rush hours than in the evening. Therefore, we may deduce that shared bikes in Singapore do serve as a “last-mile” solution although to a limited extent.

Cycling activities on weekends are generally less intensive in the early morning. The correlation analysis for arrival trips suggests that areas where commercial activities proliferate are associated with lower attractiveness in the early morning but increased popularity later on. Urban locations with a dense road network tend to attract more cyclists during the daytime. The analysis for departure trips suggests that MRT stations produce fewer trips in the morning, and dense housing areas are associated with a morning activeness (08:00–10:00).

Finally, we visualize the spatial distribution of squares with distinctive temporal patterns and discuss location-specific insights. On weekdays, there exists a universal pattern among most of the MRT squares, where higher attractiveness is observed in the early morning. On weekends, however, they show diverging patterns. MRT squares in the CBD — the central area of Singapore — tend to attract more trips in the afternoon and particularly in the evening, while the outer ones — where many residential neighborhoods are located nearby — receive more cyclists in the morning. Such a geographic difference aligns well with the rhythm of human activities. In the morning, cyclists from residential areas ride to nearby MRT stations, from which many people are taken to the central Singapore for weekend activities (e.g., shopping and dining). At the end of the day, these activity locations start to produce more cycling trips, taking people to nearby transit stations which lead to their final destinations. In addition to the above findings, most of the residential neighborhoods serve as active morning producers on both weekdays and weekends. Beyond this knowledge that is more or less expected, these neighborhoods can be better distinguished through their 2^{nd} PCs, which suggest a dichotomy that further reveals their respective active periods.

This study demonstrates how eigendecompostion can be used to better understand the temporal rhythms of shared bike usages as well as the variations across urban locations. Although other approaches, such as unsupervised classification, have been employed to tackle similar questions for station-based systems (Froehlich et al., 2009; Vogel et al., 2011), the eigendecomposition approach could have its own advantage over these methods for studying dockless bike-sharing systems. As bicycles are unleashed from docking stations, the improvement in bicycle accessibility will produce a more continuous cycling surface as compared to traditional systems with rental stations. In a dockless bike-sharing system, places that are nearby might exhibit smooth transitions in their temporal usage patterns. These transitions are sometimes difficult to capture based on unsupervised classification methods (e.g., K-means, hierarchical clustering) due to the nature of these algorithms. The eigendecomposition and principal component analysis could capture these subtle differences by highlighting their structural variations along the eigenvectors. Although this study does not compare the above algorithms, it is worthwhile to perform comparative analysis in the future to further evaluate their effectiveness. Nevertheless, the workflow developed in this research can be applied in other cities to better understand the dynamics of this new generation system as well as the implications for urban design and transport planning.

This work also points to a future research direction that we aim to pursue. Currently, the temporal variations of cycling activities at each location are averaged over weekdays or weekends to produce a representative curve. This allows us to study usage levels of shared bikes over the 24 h. However, the day-to-day variations at each location remain unexplored. Many exogenous factors — such as weather, land use, promotion of bike-sharing operators, and other special events — could affect the regularities of a location's diurnal patterns. Understanding these regularities or irregularities could provide additional insights into the locations' temporal behaviors, which further support applications such as short-term travel demand forecast and bicycle dispatch for resource optimization.

Acknowledgement

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Appendix A. Linear combination of eigenvectors - examples

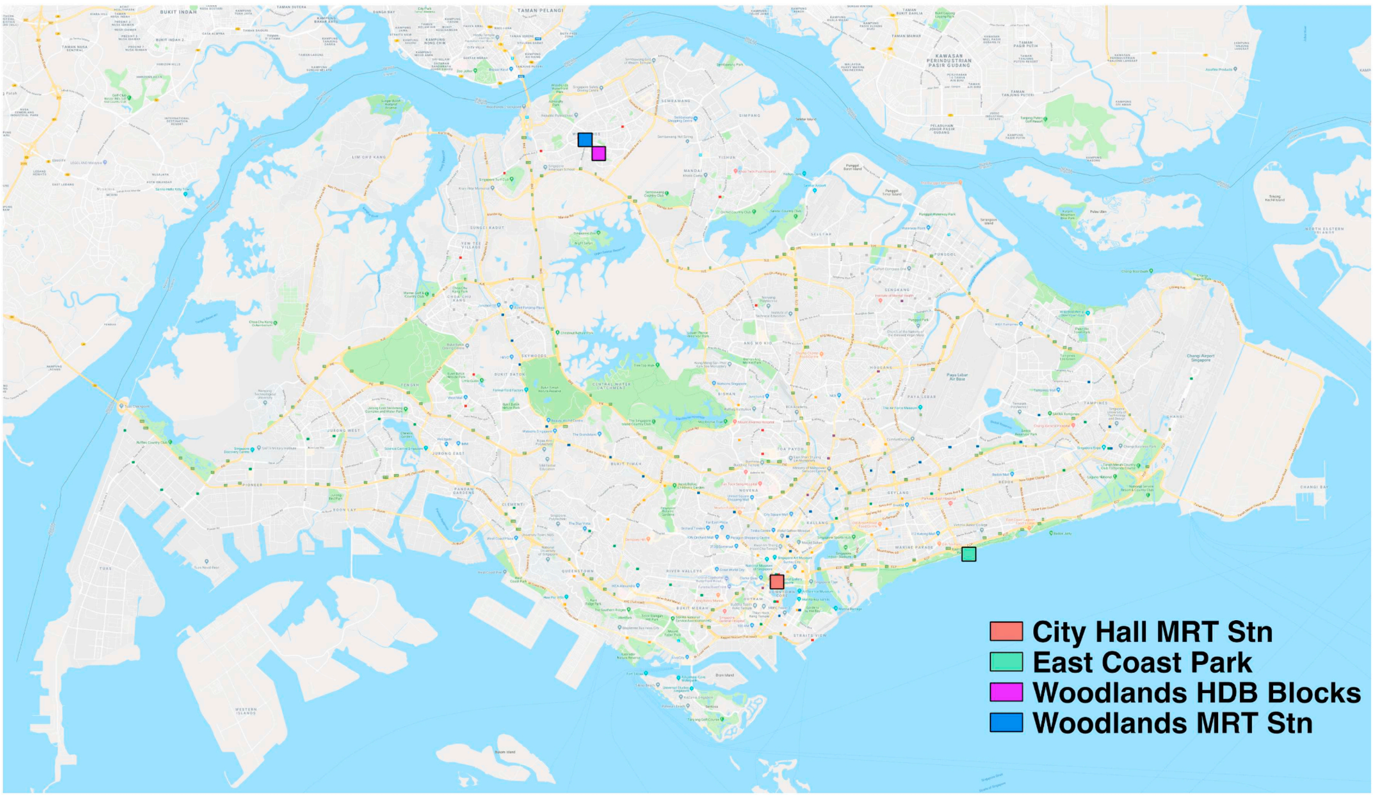

Fig. A.1. Four selected squares in Singapore.

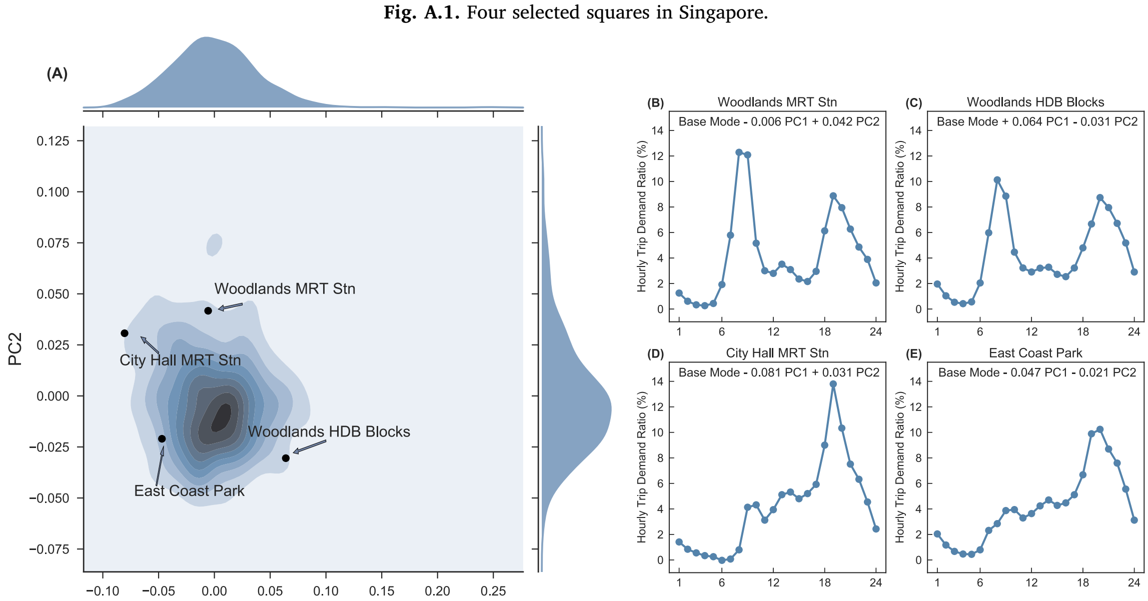

Fig. A.2. (A) Joint distribution of PC1 and PC2 coefficients of the squares (weekday departure trips); (B–E) Temporal patterns of the four locations reconstructed from these two PCs.

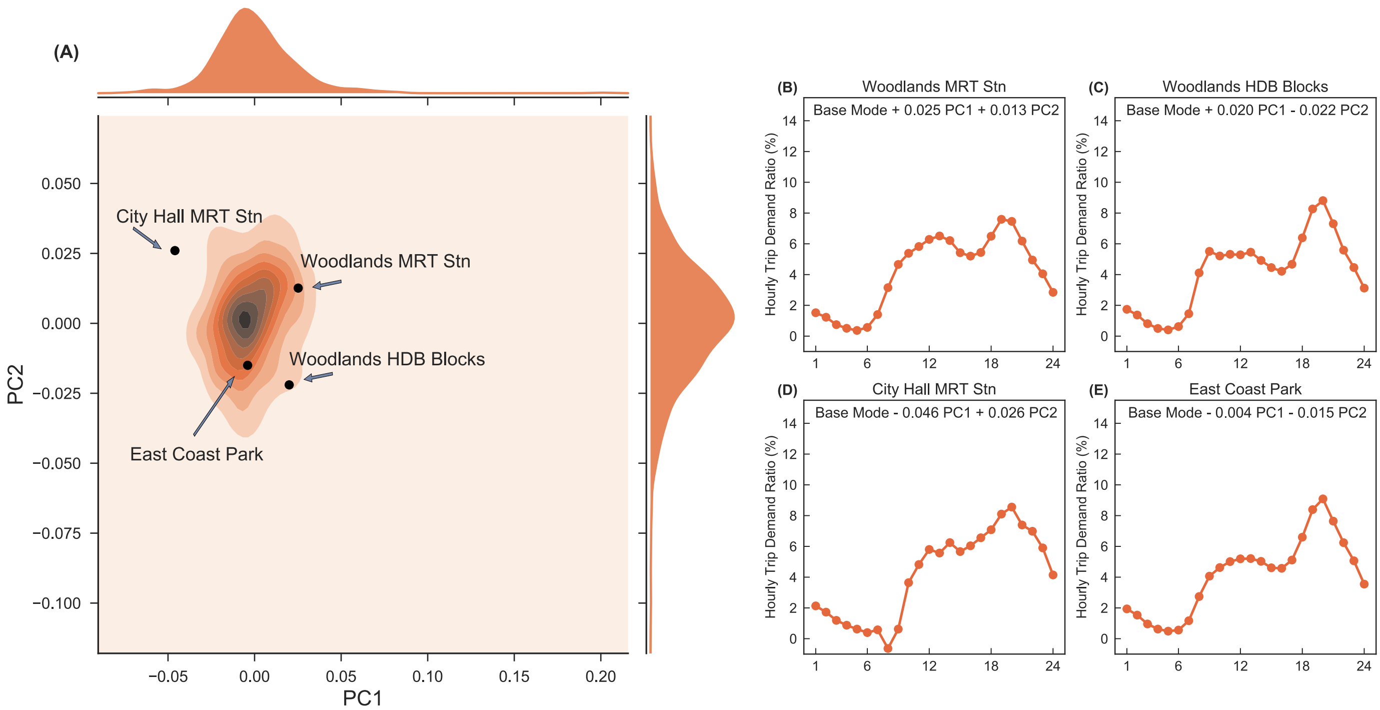

Fig. A.3. (A) Joint distribution of PC1 and PC2 coefficients of the squares (weekend arrival trips); (B-E) Temporal patterns of the four locations reconstructed from these two PCs.

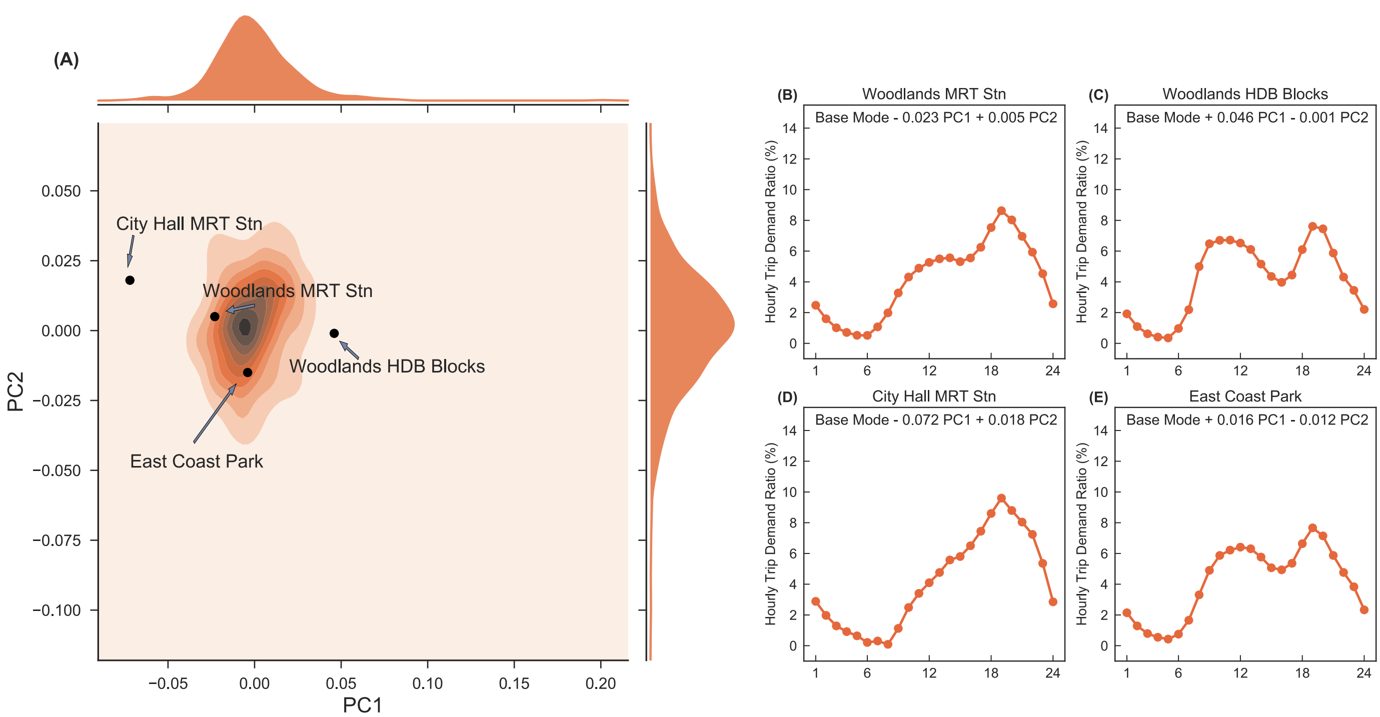

Fig. A.4. (A) Joint distribution of PC1 and PC2 coefficients of the squares (weekend departure trips); (B–E) Temporal patterns of the four locations reconstructed from these two PCs.

Appendix B. Scree plot of eigendecomposition

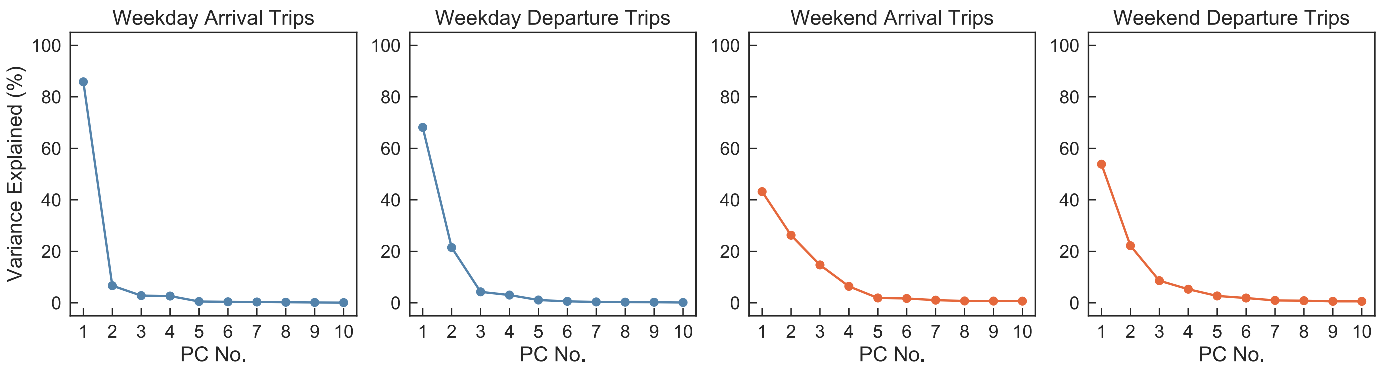

Fig. B.1. Fraction of total variance explained by the PCs.

Appendix C. Correlations between built environment indicators and each of the two PCs

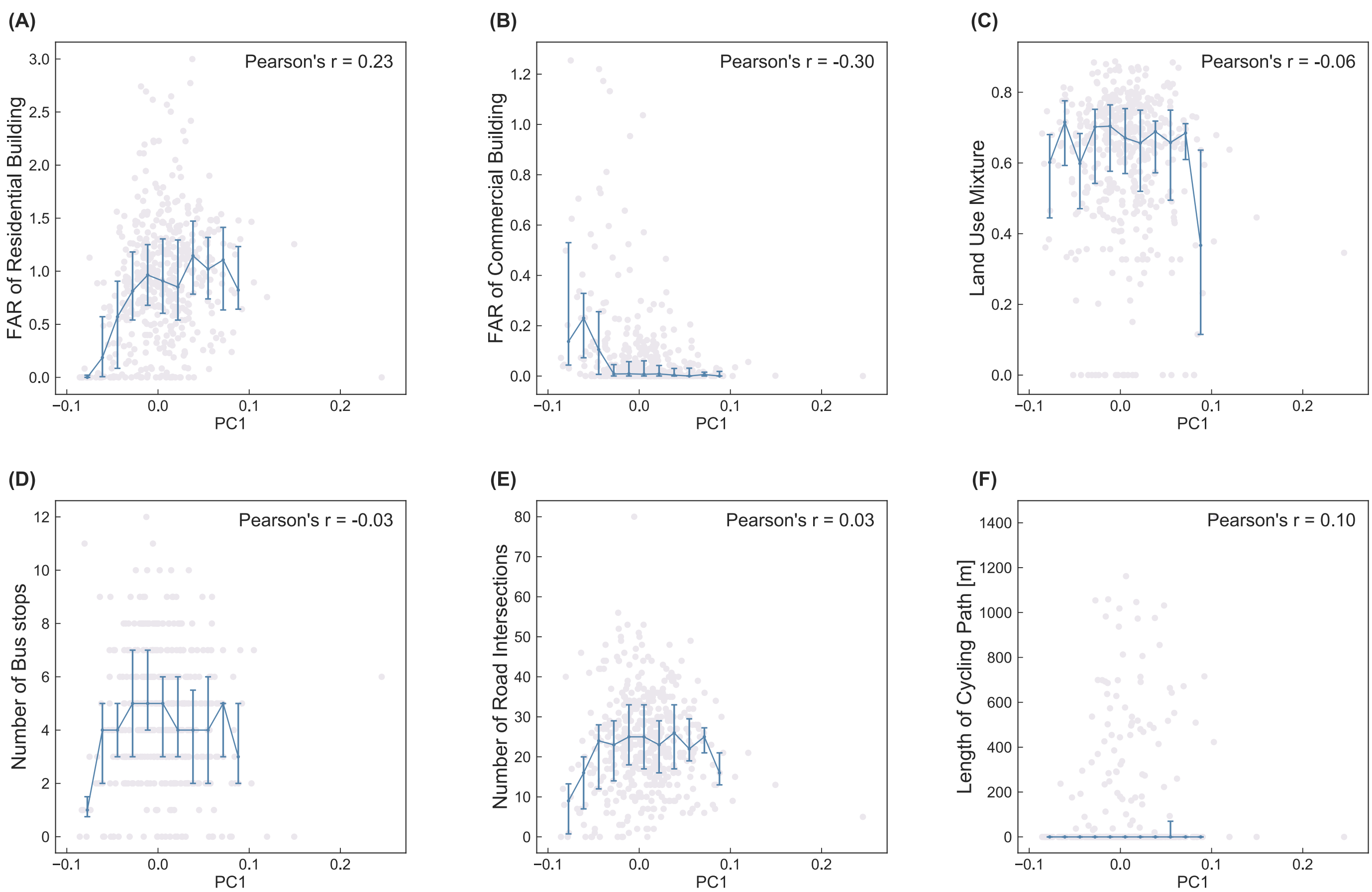

Fig. C.1. Correlation between built environment indicators and PC1 coefficients — Weekday departure trips.

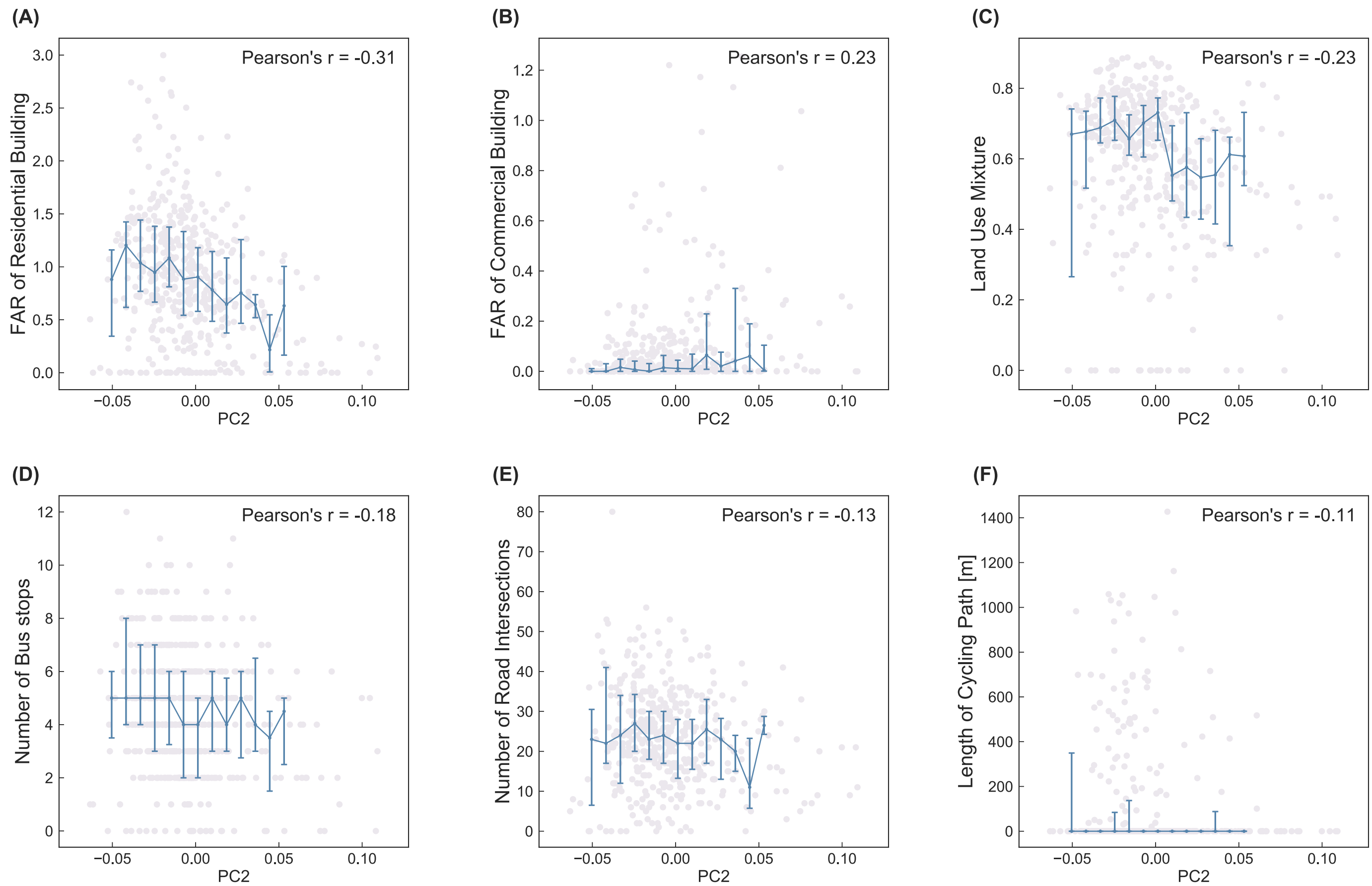

Fig. C.2. Correlation between built environment indicators and PC2 coefficients — Weekday departure trips.

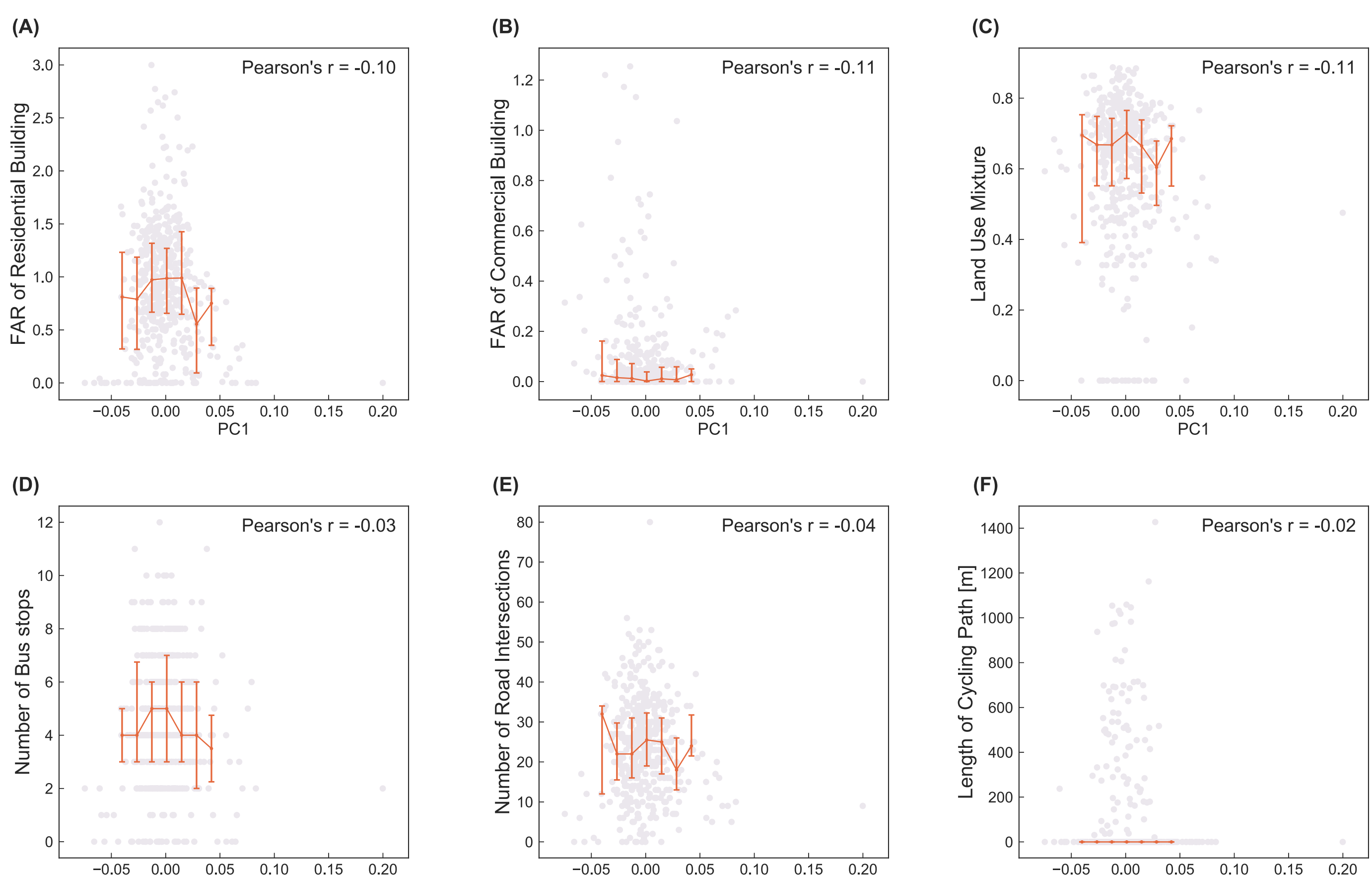

Fig. C.3. Correlation between built environment indicators and PC1 coefficients — Weekend arrival trips.

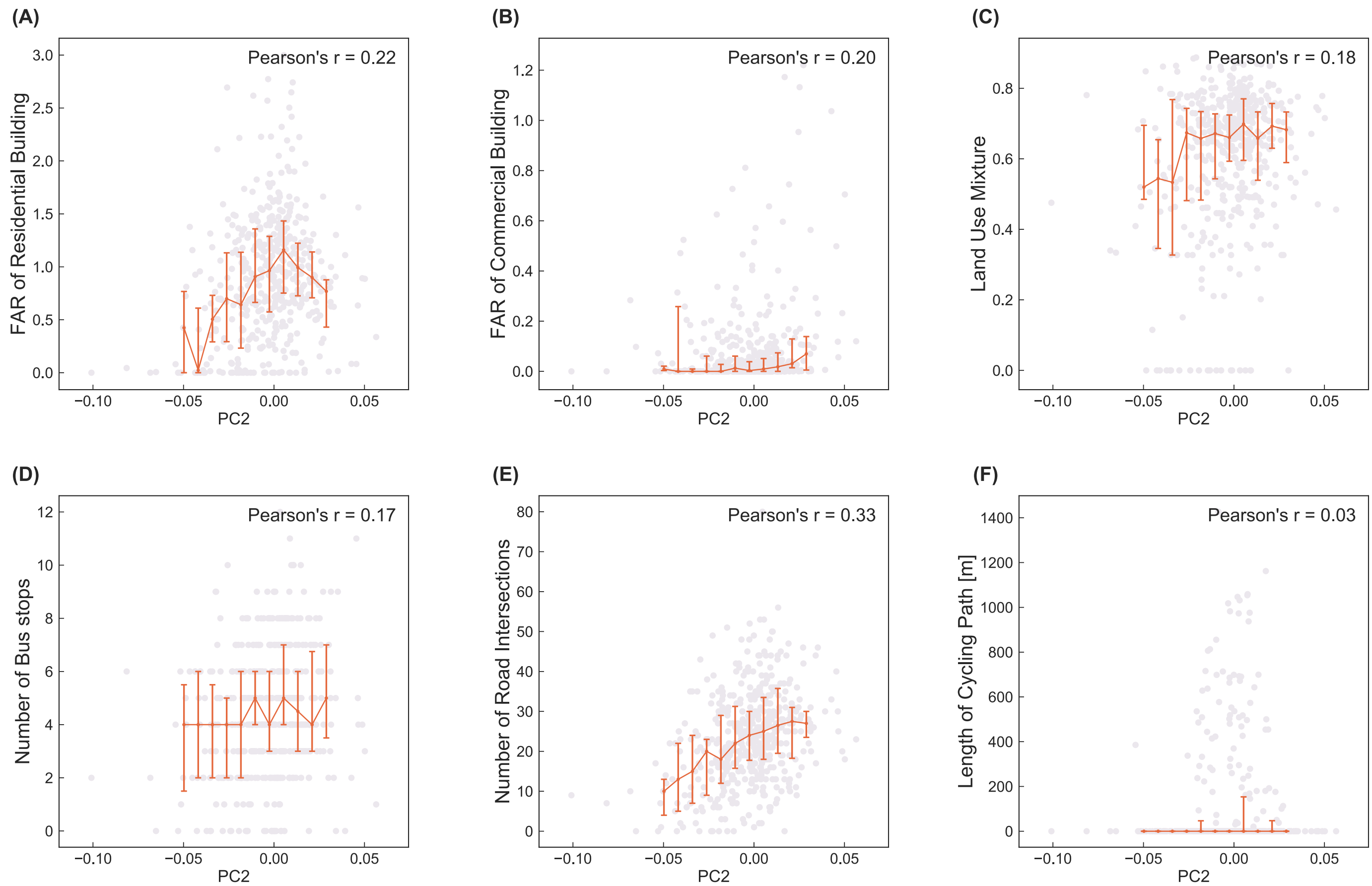

Fig. C.4. Correlation between built environment indicators and PC2 coefficients — Weekend arrival trips.

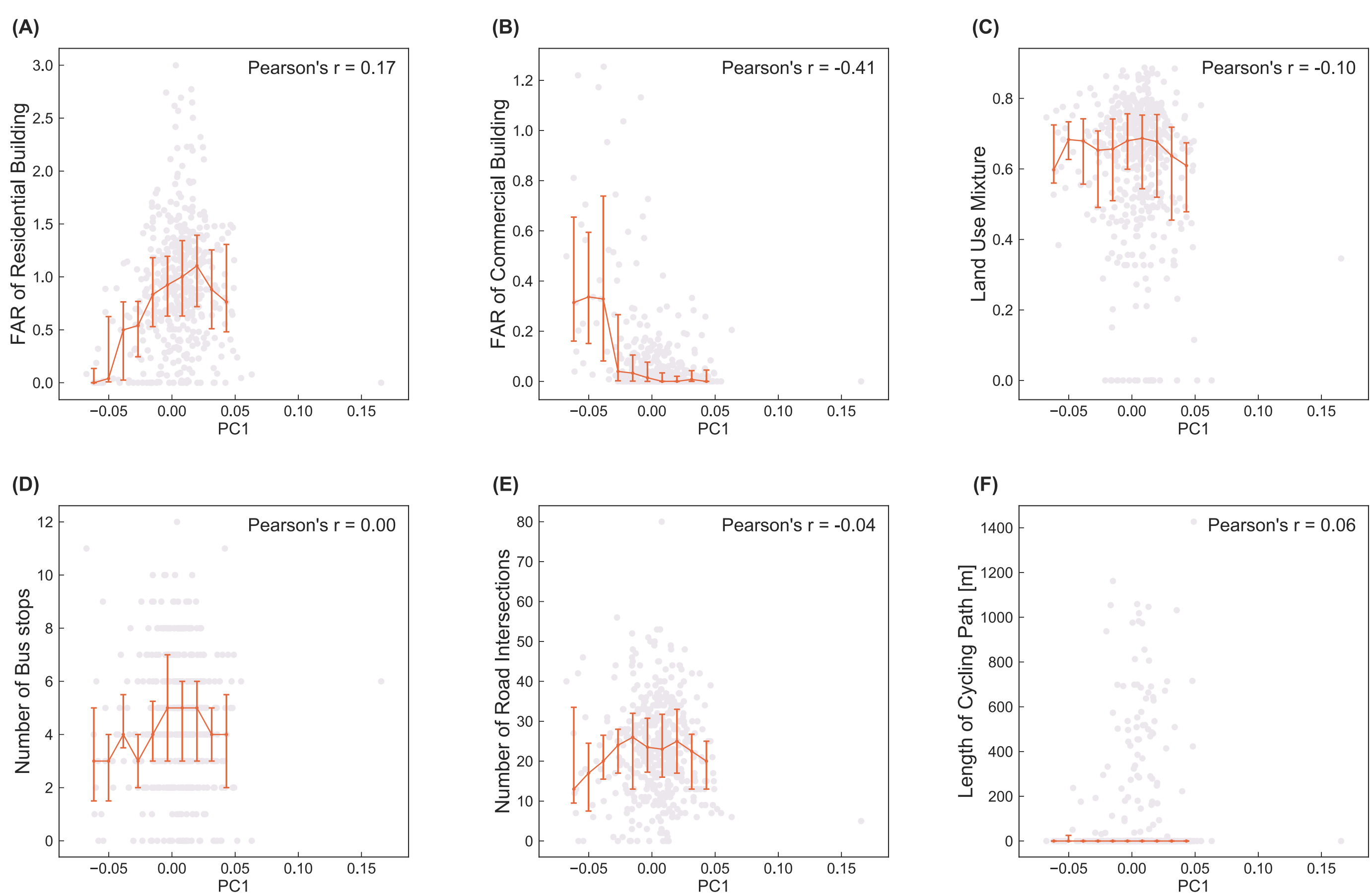

Fig. C.5. Correlation between built environment indicators and PC1 coefficients — Weekend departure trips.

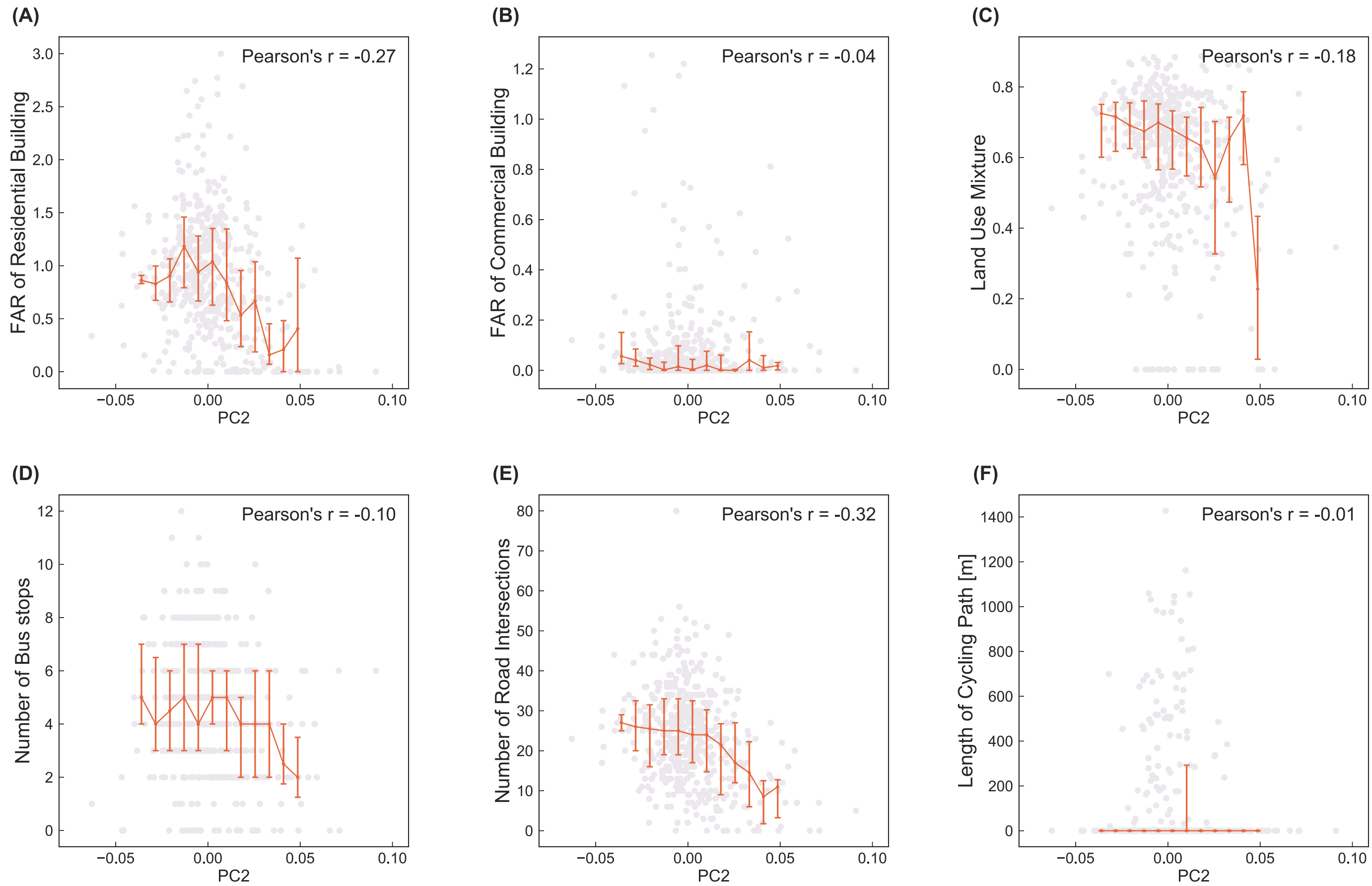

Fig. C.6. Correlation between built environment indicators and PC2 coefficients — Weekend departure trips.

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