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Do people walk more in transit-accessible places?

Yunkyung Choi
Georgia Institute of Technology
yunkyung.choi@gatech.edu

Subhrajit Guhathakurta
Georgia Institute of Technology
subhro.guha@design.gatech.edu

Abstract: While transit-oriented developments (TODs) are generally believed to promote the use of sustainable travel modes, the degree to which various components of TODs influence travel behavior is still debatable. This paper revisits Chatman's (2013) question: "Does TOD need the T?" by addressing the effect of rail transit access in influencing walking behavior in TOD areas. In particular, we compare TODs to other similar areas, with rail transit access being the key variable, and examine whether people are more likely to walk in TODs for purposes other than transit use. This hypothesis is tested using traffic analysis zones (TAZs) in the Atlanta Metropolitan Region. First, we identify TAZs within rail catchment areas and use propensity scores to match them with other TAZs with similar built environmental characteristics except for rail transit access. We then conduct a statistical analysis comparing walking trips for both commuting and non-commuting trips in these two TAZ groups. Our results confirm that the likelihood of walking trips increases in transit-accessible TAZs compared to other similar areas without transit. Therefore, states and localities can maximize the benefits of pedestrian-friendly built environments by making rail transit access an important part of their planning and design.

Keywords: Transit-oriented development, transit access, walking, travel behavior, built environment

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1 Introduction

The vast and growing literature on the relationship between built environment and travel behavior has generally indicated that particular urban forms, such as transit-oriented development (TOD), encourage the use of public transit and non-motorized transportation (Greenwald & Boarnet, 2001; Ewing & Cervero, 2010). TOD refers to the design of residential and commercial areas around transit stations that maximizes transit access and minimizes automobile use. These areas tend to be high-density

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areas with mixed-land uses that are pedestrian-friendly. Several studies have shown that proper design of TODs encourages people to own fewer vehicles, drive less, and use more non-motorized modes of travel (Pushkarev & Zupan, 1977; Cervero, Murphy, Ferrell, Goguts, & Tsai, 2004; Evans, Pratt, Stryker, & Kuzmyak, 2007; Haas, Miknaitis, Cooper, Young, & Benedict, 2010; Suzuki, Cervero, & Iuchi, 2013; Gallivan, Rose, Ewing, Hamidi, & Brown, 2015). These studies also identified high-density, mixed-use, pedestrian-friendly environments, and quality public transit facilities and service as key characteristics of TODs that encourage people to drive less and walk more. In general, researchers have found a high correlation between TODs and walking activity. However, the question that still remains inadequately addressed is whether increased walking is related to the characteristics of urban form in the TODs independent of transit access. In other words, we are echoing Chatman's (2013) question: "Does TOD need the T?"

Given that we both examine the impact of transit access in TODs, Chatman's paper is highly relevant to this discussion, but the objective of his study was somewhat different from the purpose of this paper. While his study focuses on automobile miles driven in TOD areas, we examine walking activities that originate from such areas in this paper. Because researchers have focused primarily on testing the effects of TODs on automobile and transit use, we are relatively in the dark regarding the specifics of walking behavior in TODs. The limited number of studies that have tried to examine the impact of TODs on walking behavior focused predominantly on ingress and egress modes of walking to transit, primarily for commuting (Loutzenheiser, 1997; Alshalalfah & Shalaby, 2007). Since commute travel accounts for a relatively small proportion of all travel, the impact of TODs on non-work-related walking behavior remains largely unknown. In fact, the share of commuting trips in 2017 was 7.8% of total walking trips, whereas non-work/school-related walking trips accounted for 81.6% (U.S. Department of Transportation, 2017). In Atlanta, the percentage of non-work/school-related walking trips was approximately 61% in 2011, which was lower than the national average at the time but significant nonetheless. Therefore, an analysis of non-work-related walking behavior in addition to the existing studies on commuting trips can offer valuable insights on sustainability and community health in TOD areas.

This paper aims to investigate the relationship between various characteristics of TODs and the prevalence of walking trips for purposes other than transit use by testing the hypothesis that rail transit access by itself would generate more walking trips regardless of built environment characteristics. To achieve said objective, we first divided traffic analysis zones (TAZs) into two groups. The first group consists of TAZs within the catchment area of the Metropolitan Atlanta Rapid Transit Authority (MARTA) rail stations, and the other group consists of TAZs outside the catchment area. We then identified pairs of TAZs from the two groups that have similar built environment characteristics, making rail transit access the key differentiator. A propensity score matching method was employed to compare the built environment features of various TAZs. Finally, we excluded ingress and egress trips to and from transit stations and examined the remaining walking trips that originate from these two TAZ groups while controlling for sociodemographic and travel characteristics. This modeling approach allows us to determine whether the presence of rail transit, independent of built environment characteristics, has a significant influence on walking behavior. In conclusion, we found a strong positive association between the presence of rail transit access and the level of walking activity for both commuting and non-commuting trips, ceteris paribus, which may have significant planning implications.

2 Literature review

2.1 Prevalence of walking trips and behavioral theories

There are two theoretical propositions—behavioral spillover effects and social interaction effects — that can provide guidance to addressing "Why higher level of walking activities for purposes other than transit use is expected in TOD areas than in non-TOD areas ever after controlling for built environmental and demographic characteristics."

In the field of economics and psychology, the theory of behavioral spillover effects has gained a substantial foothold in recent years. According to the theory of behavioral spillover effects, each behavior influences the next in that one behavior engenders a similar or complementary behavior that follows (Dolan & Galizzi, 2015). Often, the sequence of behaviors is pre-planned to ensure that they can be executed with high efficiency and minimum obstructions. In the case of a trip chain, people tend to decide the travel mode by considering the entire tour that includes the first and last trips as well as intermediate stops (Frank, Bradley, Kavage, Chapman, & Lawton, 2008). In essence, if a person walked to a transit station from home, she is more likely to walk back home. Based on the behavior spillover theory, walking trips to and from transit stops, which are common in neighborhoods with transit stations, may lead to other walking trips, such as picking up a child or groceries on the way home, simply because they are in the same trip chain. In fact, the theory of behavioral spillover has already been applied to travel behavior related studies in examining the relationship between an individual's climate-relevant behavior and travel mode choice (Lanzini & Thøgersen, 2014; Lanzini & Khan, 2017).

The theory of social interaction effects, on the other hand, captures the propensity of individuals to behave similarly to others in their vicinity, and this sociological concept has been widely used in the fields of economics and psychology as well. In his study, Manski (2000) identified two types of social interactions – endogenous and exogenous (contextual) – to explain why people in the same group tend to behave similarly. He argued that endogenous interactions lead to a similarity in behavior because of the presence of a dominant behavior within the group and that exogenous interactions result in similar behavior due to the social characteristics of the group. A popular example of endogenous interactions is Schelling's residential segregation, which describes individuals' propensity to live in neighborhoods where the share of residents of their own race is above a certain threshold (Manski, 1993). Low graduation rates in more impoverished communities and high graduation rates in more affluent neighborhoods are both examples of exogenous interactions. When we apply this concept to walking mode choice decisions, endogenous interactions exist if a person's propensity to walk increases with the number of neighbors who walk, and exogenous interactions are present if a person's propensity to walk relies on the socioeconomic attributes of those neighbors (Goetzke & Andrade, 2010).

Of the two kinds of social interactions, the presence of endogenous interactions has been more widely applied to explain various travel related observations. For instance, Young (1996) showed that endogenous interactions heavily influence the formation of driving conventions in the absence of road laws. In his study, Young found that the choice of each driver between driving on the left or the right side of the road depends on the other drivers' decision on the same road. A similar example is provided by Sidharthan, Bhat, Pendyala, and Goulias (2011), who found that parents tend to allow their children to walk to school if many other children in the same neighborhood walk to school. Notwithstanding many other factors, such as safety and supportive infrastructure, that influence a parent's decision to allow their children to walk to school, Sidharthan et al. (2011) claimed that the prevalence of walking to school created a favorable environment for walking, which in turn had a significant positive effect on a parent's mode choice. Based on this premise that social interactions affect travel behavior, endogenous interactions across individuals may also arise in clusters around transit stations because these areas generally have larger pedestrian traffic. In such environment, people who are not necessarily transit riders may be influenced by the high frequency and volume of walking activities around transit stations.

The other possible explanation for the prevalence of walking in transit-accessible places is car shedding. When alternative travel modes become more attractive in terms of convenience, cost, and time efficiency, people may shed all or some of their vehicles (Carroll, Caulfield, & Ahern, 2017). TOD is a policy incentive to encourage people to drive less by providing more sustainable modes of transport. If those using rail transit to get to and from work eventually shed their vehicles, they would naturally walk more for other purposes or activities.

Unfortunately, these propositions have received very little attention in empirical studies despite their theoretical relevance. In this paper, we break new ground by examining whether the presence of rail transit stations in TOD areas leads to increased walking activities after excluding ingress and egress trips to and from the station.

2.2 Transit-oriented developments and their impact on travel behavior

There are many different definitions of TODs, but most agree that TODs refer to compact, mixed-use developments with walkable environments within a specified geographical area near transit services (Calthorpe, 1993; Bernick & Cervero, 1997; Boarnet & Crane, 1998; Parker, 2002; Cervero, Ferrell, & Murphy, 2002; Cervero et al., 2004). As discussed extensively in the literature, the identification of TODs depends on the assessment of a variety of land-use characteristics, which are often referred to as the "D" variables (Austin, et al., 2010; Kamruzzaman, Baker, Washington, & Turrell, 2014; Nasri & Zhang, 2014; Higgins & Kanaroglou, 2016; Ralph, Voulgaris, Taylor, Blumenberg, & Brown, 2016). Cervero and Kockelman (1997) coined the term "three Ds," which stands for development density, land-use diversity, and pedestrian-friendly design. Studies from later periods built on this idea and introduced a four "D" variables system: destination accessibility, distance to transit, demand management, and demographics (Ewing & Cervero, 2010).

The proponents of TOD believe that TODs can contribute to relieving various urban problems such as traffic congestion, air pollution, affordable housing shortages, and sprawl (Cervero et al., 2002). TODs, therefore, could be considered an effective solution in promoting social, economic, and environmental sustainability within communities. Most studies about TODs analyzed their impacts on travel behavior, with a specific emphasis on how effectively they reduce car usage, encourage transit ridership, and promote non-motorized travel (Cervero, 1993; Boarnet & Crane, 2001; Chatman, 2006; Arrington & Cervero, 2008; Hale, 2014; Nasri & Zhang, 2014; Ewing & Hamidi, 2014; Langlois, van Lierop, Wasfi, & El-Geneidy, 2015; Laham & Noland, 2017; Park, Ewing, Scheer, & Tian, 2018). For instance, Nasri and Zhang (2014) found that residents living in TOD areas were more likely to have between 21% and 38% lower vehicle miles traveled (VMT) than those living in non-TOD areas. Arrington and Cervero (2008) analyzed 17 TOD projects in urbanized areas and similarly observed that TOD commuters typically took transit about two to five times more than other commuters in the region. Also, Langlois et al. (2015) found that newcomers in TOD areas were more likely to use sustainable travel modes for amenities and leisure trips.

While TODs are generally believed to promote the use of non-auto travel modes, there is some debate about the degree to which various components of TODs influence travel behavior of residents living in such areas. Cervero (1993) claimed that proximity to a transit station effectively promotes more transit ridership than what can be expected from just a mixed-land use and walkable environment. Laham and Noland (2017) also found that proximity to transit stations leads to more walking for restaurants—coffee trips and grocery—food shopping trips. In addition, Arrington and Cervero (2008) found that the mixed land use attribute of TOD is a key factor in facilitating transit use for various trip purposes and that the combination of high population/employment density and small-sized street blocks encourages more transit use. Similarly, Vale and Pereira (2016) claimed that the built environment of a workplace and its accessibility have significant effects on walking behavior. Elsewhere, Park et al. (2018) found that transit accessibility, land-use diversity, and street network design of a station area are strongly associated with transit use and walking but density not so much.

Some studies have also suggested that residential self-selection is a major determinant of non-auto-based travel of residents in TOD areas (Cervero et al., 2002; Bhat & Guo, 2007; Cao, Mokhtarian, & Handy, 2009; Salon, 2015). The idea underlying the concept of residential location choice is that people tend to live in neighborhoods where their travel needs and preferences are satisfied. Cervero et al. (2002) observed that TODs experience demographic changes over time, such as increasing numbers of childless couples, growing shares of people who want to downsize their living space, and increasing influx of foreign immigrants who may come from countries with a preference for transit-oriented living. In other words, TODs attract particular types of households that seek higher levels of transit accessibility. This group of researchers addressed that empirical results may be biased without controlling for residential self-selection when evaluating the relationship between built environments and travel behavior.

Another group of researchers, while admitting the presence of self-selection, claimed that the effect of self-selection is limited compared to other more dominant factors related to TODs (Chatman, 2009; Nasri, Carrion, Zhang, & Baghaei, 2018). Nasri et al. (2018) found that self-selection accounted for roughly 40% of the effect of TODs in lowering auto trips in both Washington, D.C. and Baltimore. Despite the considerable effect of self-selection, they found that TOD still plays an important role in influencing the mode choice of residents. Chatman (2009) also found that residential self-selection tends to enhance built environmental influences rather than diminish those impacts, which suggests that the presence of self-selection may actually downplay the impacts of built environment.

The key takeaway from the above literature review is that most studies have primarily focused on the relationship between the various characteristics of TODs and the reduction in automobile usage or the increase in transit use. Others have also analyzed the use of non-motorized travel in TOD areas (Greenwald & Boarnet, 2001; Rodríguez & Joo, 2004; Schwanen & Mokhtarian, 2005; Joh, Chakrabarti, Boarnet & Woo, 2015; Durand et al., 2016), but their studies were limited to walking access to and from transit only. This paper seeks to identify the relationship between TODs and walking trips that do not involve transit use. Specifically, it aims to determine whether the presence of rail transit plays a unique role in influencing walking behavior.

3 Data and methods

3.1 Propensity score matching

This study employs propensity score matching (PSM), which is a method used in comparative studies to construct control groups that are matched with treated groups with respect to the observed characteristics. PSM is widely used in various fields including social sciences and economics, in which a randomized experiment is often limited. Unlike controlled experiments, observational studies do not allow for random assignment of treatments to the population, which introduces a bias in estimating the treatment effect. PSM provides an opportunity to mitigate such bias by balancing the distribution of observed characteristics of control groups corresponding to treated groups using propensity scores, thus providing more precise estimates of the true treatment effects (Rosenbaum & Rubin, 1983). The propensity score is a single scalar that is estimated from a probit regression, where such scores measure the conditional probability of selecting the treatment (Thoemmes & Kim, 2011). The major advantage of using PSM, it finds matched groups based on the propensity scores that integrates all the covariate information regardless of the number of covariates in the model (D'Agostino Jr., 1998). In conventional matching techniques, it is difficult to find close matches between treated and control groups when many covariates are included in the model that increases the dimensionality of matches.

The objective of PSM in this study is to find two TAZ groups that have similar built environment characteristics but are distinguished by the presence or absence of a transit station. Before applying the PSM analysis, we followed several steps for data preparation. First, we identified which TAZs are located within a rail catchment area. The catchment area is defined as a one-mile walking distance along the street network from the nearest rail station to the centroid of each TAZ. To identify catchment areas, we used the OSMnx street network that is based on OpenStreetMap. Among different OSMnx network types, we employed the walk network that includes all streets and paths for pedestrian use. We then applied PSM to match TAZs within rail catchment areas (treated group) to TAZs without access to rail stations (control group) based on its built-environmental attributes. Since PSM only accounts for observed covariates, any missing data or latent variable may lead to biased estimates (Garrido et al., 2014). To reduce bias, we included built environment attributes that were commonly used in previous studies. As a result, a binary probit model to estimate propensity scores includes the following "D" variables: activity density, balance between population and all jobs (or retail/service jobs), land-use diversity, intersection density, proportion of four-way intersections, average block length, sidewalk density, open space access, and transit access to bus stops. A binary treatment variable in the probit model takes the value of 1 when the TAZ is located within a rail catchment area and 0 otherwise. In estimating the propensity scores, we used 1:1 matching for the nearest neighbor with replacement option and a caliper of the 0.25 standard deviation of the propensity scores of treated TAZs.

To check for the robustness of PSM, we evaluated the balance between treated and control groups. The results of PSM often exhibit a substantial overlap between treatment and control groups when the sample size is limited (Stuart, 2010). Although the minimum requirement of sample size for PSM has not yet been determined, existing literature suggests evaluating the balance between the covariates in two groups with a standardized difference, which is the mean difference. The standardized difference is calculated as follows: $(\bar{x}_t - \bar{x}_c)/\sqrt{\{(s_t^2 + s_c^2)/2\}}$ where $\bar{x}_t$ refers to the mean of the treated cases, $\bar{x}_c$ the mean of the control cases, s_t and s_c the corresponding standard deviations (d'Agostino, 1998). According to Rubin (2001), the absolute standardized difference in means should be less than 0.25. To satisfy this recommendation, we reduced the caliper of PSM from 0.25 to 0.10 standard deviation of the propensity scores of treated TAZs.

Data for PSM analysis were extracted from a variety of sources, and Table 1 contains a list of built environment variables and corresponding descriptions of measurement at TAZ level. For sociodemographic and employment information, we used the 2007-2011 American Community Survey (ACS) 5-year estimates (https://www.census.gov/programs-surveys/acs) and the 2011 Longitudinal Employer Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) (https://lehd.ces.census.gov/data). To measure the characteristics of land use, we use the 2014 Tax Parcel Records for Fulton and DeKalb Counties. From the Atlanta Regional Commission (ARC) (https://opendata.atlantaregional.com), we used the 2006 green space data for open space access and the 2016 ARC transit stop information for bus and rail transit. The 2016 OpenStreetMap (OSM) (http://download.geofabrik.de/north-america/us.html) was used for road network and sidewalk information. The OSM data has been frequently used to calculate street network characteristics because it is open-source and up-to-date. However, the quality of OSM data has been a concern because the data are collected by volunteers who are not trained in data collection procedures. The limited ability of the volunteers may result in incomplete and inconsistent data, and missing street or sidewalk information in the OSM data may cause lower intersection or sidewalk density than the actual level. Despite its limitation, the OSM data is still a powerful source of information due to its high coverage that includes areas where official data is not available. Also, previous studies on assessing the completeness of OSM data found that street and sidewalk information has been increased in the OSM platform, making the data more complete. In fact, the OSM data imported TIGER/Line as a foundational data source in 2008, and numerous improvements have been made by including additional features such as sidewalks and bike lanes (Craun & Chih-Hung, 2017; Zielstra, Hochmair, & Neis, 2013).

Table 1. Measures of built environmental characteristics

Variable	Description
Activity density	This variable measures the sum of population and employment per acre in TAZ.
Jobs (or retail/service jobs) to population balance	These variables measure all jobs (or retail/service jobs) to population ratio in a TAZ as compared to the same ratio in the county as a whole. It ranges from 0 for a TAZ with residents but no jobs (or only jobs, no residents) to 1 for a TAZ with the same ratio of all jobs (or retail/service jobs) to the population as that of the county as a whole. It is calculated from the following equation: $$B_{TAZ} = 1 - \lvert (S_{TAZ} - aP_{TAZ}) / (S_{TAZ} + aP_{TAZ}) \rvert$$ where: B_{TAZ} = Jobs (or retail/service jobs) to population balance in TAZ; S_{TAZ} = Jobs (or retail/service jobs) in TAZ; P_{TAZ} = Population in TAZ; and a = The ratio of jobs (or retail/service jobs) to population in the county.
Land-use diversity	Inverse Simpson's index of diversity is computed to derive land-use diversity based on six land-use categories. These categories include residential, commercial, office, institutional, recreational/open space, and utilities. If land use is homogeneous, it takes a diversity score of 1, and a higher score indicates diverse land use. The index is calculated as follows: $$D_{TAZ} = 1 / \Sigma_{i=1}^{6} (n_i / N)^2$$ where: D_{TAZ} = Diversity of land use in TAZ; n_i = Total land area of land use type i in the TAZ; and N = Total land area in TAZ.
Intersection density	This variable measures the number of intersections per acre in TAZ.
Four-way intersection proportion	This variable measures a percentage of four-way intersection in TAZ.
Average block length	This variable measures the average length of blocks in TAZ.
Sidewalk density	This variable measures the length of sidewalks per square mile in TAZ. Footway and pedestrian classes in the OSM data were used to calculate sidewalk density.
Open space access	This variable is the percent of the total area in TAZ that within 1 mile of recreational/open space.
Bus stop density	This variable measures the number of bus stops per acre in TAZ.
Distance to bus stops	This variable measures the average distance to the nearest three bus stops from each residence in TAZ.
Rail transit access	This variable indicates whether or not the TAZ is located within the rail catchment area. We employed network analysis to identify TAZs which centroids are located within a one-mile walking distance from the nearest rail station.

3.2 Multi-level logistic regression model

Many studies employing PSM have examined whether treated and control groups are systematically different in travel behavior by comparing the means of the two groups. Thus, we conducted a Chi-square test of independence to examine whether the pattern of observed walking trips is significantly different between the treated and control TAZ groups. The null hypothesis of a Chi-square test is that two TAZ groups are independent in terms of walking trips. To determine the rejection of the null hypothesis, we compared the P-value to the significance level of 0.05.

However, researchers including Ho, Imai, King, and Stuart (2007) and Stuart (2010) suggest that a more meaningful result could be derived by employing regression analysis, which controls for covariates that affect the outcome of interest on matched samples. Since the combination of PSM and regression analysis provides double-robustness in removing estimation bias of treatment effect due to confounding variables, we employed a multi-level logistic regression model to compare walking behavior in the treated and control TAZs (TOD and non-TOD areas).

Among various types of logistic regressions, multi-level logistic regression analysis is a suitable approach for this study due to data structure. A multi-level model is widely used to evaluate a clustered structure where elementary units are nested within a hierarchical structure (Bhat, 2000). In this study, people in a given TAZ likely to be influenced by the walking behavior of other people in the same TAZ. Since this dependency among the observational units violates the independence assumption, standard errors of regression coefficients may be underestimated in standard logistic regression models. On the other hand, multi-level logistic regression models estimate unbiased standard errors of the regression coefficients by including cluster-level characteristics in the model to account for the dependence in a nested data structure (Raudenbush & Bryk, 2002).

Also, a multi-level model disentangles the within-cluster effects from the between-cluster effects. It distinguishes those two sources of variations by formulating a model at the macro-level of clusters in addition to the micro-level of individuals (Bhat, 2000). In this study, a multi-level model estimates two variances: 1) within-TAZ effects, the extent to which individual-level characteristics are associated with the odds of choosing to walk, and 2) between-TAZ effects, the extent to which TAZ-level attributes are related to the odds of choosing to walk. The variance of within-TAZ effects is also known as fixed effects, and the estimates of the effects are reported as odds ratios (OR). The variance of between-TAZ effects represents unobserved TAZ attributes affecting individual behaviors after controlling for the explanatory variables, called random effects.

We developed multi-level logistic regression models incrementally to test different model specifications based on the inclusion of three sets of explanatory factors: 1) sociodemographic characteristics, 2) travel-related attributes, and 3) rail transit access. The first and second models add individual-level variables, including sociodemographic characteristics and travel attributes, respectively. The final model adds TAZ-level factor, which is the rail transit access variable in addition to the second model. That is, the final model estimates the odds of walking as a function of both individual and TAZ characteristics.

The unit of analysis is individual trips, and the dependent variable is mode choice, which takes the value of 1 for walking and 0 otherwise. We analyze trip-based travel instead of tour-based travel, and we focus on walking trips that are not involved with other modes of travel on a tour. Based on this premise, walking trips to and from transit are excluded from the analysis since those trips are linked to transit trips in its tour. Thus, walking trips includes all purpose of activities except ingress and egress to stations. We develop models to examine walking trips for both commuting and non-commuting purposes that are not relevant to transit use. Non-commuting activities include shopping, eating out, household errands, health care, social, religious, and recreational purposes of activities.

The primary source of data used for this analysis is the 2011 household travel survey obtained from ARC, which was conducted as an activity-based survey following the completion of a 24-hour travel diary between February 2011 and October 2011. This data contains information on sociodemographic and travel behavior characteristics of 10,278 households in the 20 counties of the Atlanta metropolitan region. Among the 20 counties, we used data for Fulton and DeKalb, which contain all MARTA rail stations except for the airport station. The study area has 636 TAZs, and each walking trip is coded according to its origin TAZ. We selected the following individual-level variables based on existing literature and the availability of information in the ARC household travel survey. Sociodemographic characteristics include age (over 15 to 95), gender (male/female), ethnicity (non-Hispanic others/Hispanic), driving license ownership (yes/no), household income groups (from 1 to 10), and number of vehicles per household size (from 0 to 5). Travel-related attributes are represented by the trip length.

4 Analysis and results

4.1 Identifying areas with similar built environments with and without transit access

As noted earlier, this study examines the effect of transit access on the prevalence of walking in the Atlanta metropolitan region. To investigate this effect, we divided TAZs in the Atlanta metropolitan region into either the treated group (TOD areas) or the control group (non-TOD areas) using PSM so that the differences on each of the covariates across the two groups are reduced to the minimum. In this step, we run a binary probit model to estimate the probability of each TAZ being located within the rail catchment area, which is the propensity score. From the total TAZs (n=636), this study finds 73 treated TAZs and 73 control TAZs, which form pairs of comparable built environment characteristics that are distinguished by the presence or absence of a rail station. Figure 1 presents the locations of the treated and control TAZs with the coverage of MARTA rail stations in the study area.

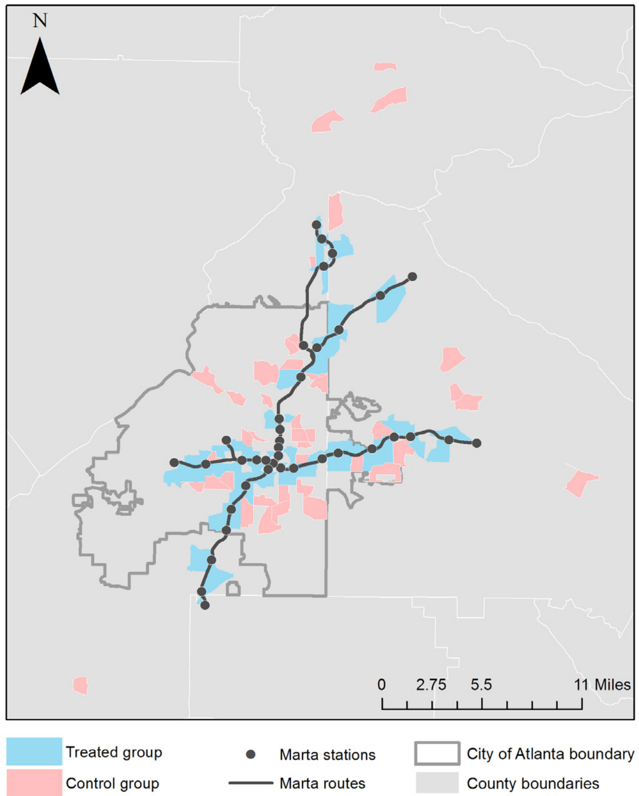

Figure 1. The location of treated and control TAZs in the study area

Figure 2 shows propensity scores before and after matching, and it reveals that PSM reduces the imbalance between treated and control TAZ groups after matching. Table 2 presents observed built environment characteristics of the treated and control TAZs before and after matching, and the balance of the covariates is checked with the standardized difference in mean. The treated and control TAZ groups show substantial initial differences in all built environmental characteristics with large standardized differences in mean. As expected, the difference in the observed built environment characteristics between the two groups was reduced after matching by having the absolute values of the standardized differences in mean below 0.25.

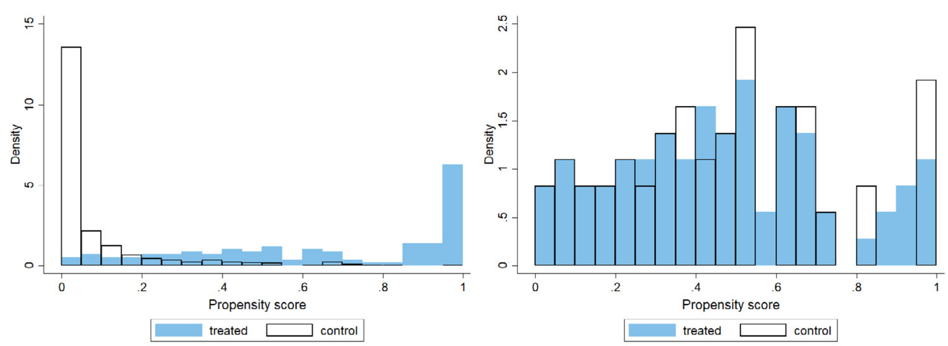

Figure 2. Propensity scores of treated and control TAZs: before (left) and after matching (right)

Table 2. Summary statistics of treated and control TAZs

Variable	Treated TAZs		Control TAZs		Std. Dif[1]
	Mean	Std. Dev.	Mean	Std. Dev.	
Before matching: the summary statistics for treated TAZs (n=118) and control TAZs (n=518)					
Activity density ((population+jobs)/acre)	62.54	114.84	6.32	6.18	**0.69**
Land-use diversity (Inverse Simpson's index)	2.32	0.93	1.77	0.66	**0.68**
Balance between population and all jobs	0.70	0.72	0.48	0.41	**0.38**
Balance between population and retail/ service jobs	0.78	0.88	0.50	0.49	**0.39**
Intersection density (intersections/acre)	0.90	0.60	0.26	0.27	**1.38**
Four-way intersection proportion (%)	0.18	0.12	0.09	0.06	**0.95**
Average block length (mile)	0.11	0.04	0.15	0.11	**-0.48**
Sidewalk density (mile/square mile)	0.18	0.17	1.08	3.13	**1.05**
Bus stop density (bus stops/acre)	0.14	0.17	0.02	0.03	**0.98**
Average distance to bus stops from each residence (mile)	0.16	0.14	1.19	1.57	**-0.92**
Open space access (%)	0.87	0.27	0.36	0.34	**1.66**
After matching: the summary statistics for treated TAZs (n=73) and matched control TAZs (n=73)					
Activity density ((population+jobs)/acre)	15.21	12.71	13.81	10.48	0.12
Land-use diversity (Inverse Simpson's index)	2.14	0.77	2.00	0.76	0.18
Balance between population and all jobs	0.49	0.55	0.48	0.34	0.01
Balance between population and retail/ service jobs	0.54	0.71	0.54	0.43	0.00
Intersection density (intersections/acre)	0.68	0.43	0.64	0.37	0.10
Four-way intersection proportion (%)	0.14	0.08	0.14	0.07	-0.04
Average block length (mile)	0.12	0.04	0.11	0.04	0.19
Sidewalk density (mile/square mile)	6.04	9.13	5.33	7.70	0.08
Bus stop density (bus stops/acre)	0.07	0.06	0.06	0.04	0.24
Average distance to bus stops from each residence (mile)	0.19	0.15	0.20	0.14	-0.10
Open space access (%)	0.82	0.32	0.87	0.17	-0.18

[1] The standardized difference is the mean difference as the average standard deviation: $(\bar{x}_t - \bar{x}_c)/\sqrt{\{(s_t^2 + s_c^2)/2\}}$ in which $\bar{x}_t$ refers to the mean of the treated cases, $\bar{x}_c$ the mean of the control cases, and s_t and s_c the corresponding standard deviations. Boldface numbers indicate absolute values > 0.25.

Figure 3 shows satellite images of two matched pairs in the study area. TAZ image "a" is matched with TAZ image "b" near the Ashby station due to similar built environment attributes. For instance, both TAZs have high density and balanced land-use mix between housing and employment locations. These areas also consist of mid- to high-rise buildings of various uses and have well-connected networks to support a high volume of the active mode of transport. Similarly, TAZ image "c" is matched with TAZ image "d" where the Hamilton E. Holmes and West Lake stations are located. These TAZs are located in primarily residential districts with lower densities, and there are small-scale mixed-use developments around the station areas and few areas of pedestrian connectivity.

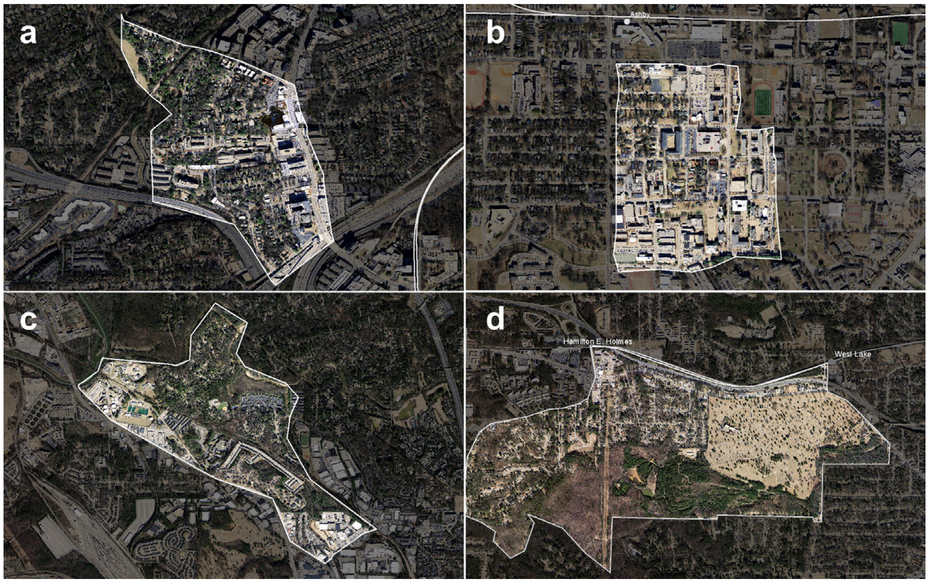

Figure 3. Examples of matched control TAZs (left) and treated TAZs (right)

4.2 Walking behavior in transit-accessible places

The travel survey data for the matched sample shows a higher percentage of walking trips in the treated TAZs within rail transit catchment area than those in the control TAZs without rail transit access, as shown in Table 3. In the treated TAZs, walking trips account for 9.8% of total trips, while those in the control TAZs account for only 7.8%. The significant result of the Chi-square test ($\chi 2$ = 8.95, p = 0.002) indicates that two groups—control TAZs and treated TAZs—have a statistically significant difference in walking trips.

Table 3. Number of trips in the study area

	Non-walking trips		Walking trips		Total trips	
	n	%	n	%	n	%
Control TAZs	2,486	92.2	209	7.8	2,695	100.0
Treated TAZs	4,113	90.2	449	9.8	4,562	100.0
Total trips	6,599	90.9	658	9.1	7,257	100.0

This information, however, does not tell us the relative importance of various factors that impact walking trips for both commuting and non-commuting activities. Thus, we examine the relationship between walking behavior and the presence of rail transit access by employing multi-level logistic regression models. Table 4 presents summary statistics for 6,436 observations, and these are broken down by two types of activities: 1) commuting trips and 2) non-commuting related trips. Descriptive statistics between the treated TAZs and control TAZs show that the mean values of walking trips for both commuting and non-commuting purposes are higher in the treated TAZs. While the mean value of trip distance for commuting purpose is lower in the treated TAZs, that of trip distance for non-commuting purpose is higher in the treated TAZs. Other variables have relatively similar mean values between treated TAZs and control TAZs.

Table 4. Summary statistics of all trips except transit access & egress trips

Variable	All trips in treated TAZs		All trips in control TAZs	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev**
Commuting purpose: number of trips in treated TAZs (n=644) and control TAZs (n=696)				
Walking trip (1=walk, 0=other modes)	0.15	0.35	0.08	0.28
Age	44.07	12.20	45.26	11.66
Gender (1=female, 0=male)	0.44	0.50	0.48	0.50
Hispanic (1=Hispanic, 0=non-Hispanic)	0.04	0.20	0.08	0.28
License ownership (1=yes, 0=no)	0.97	0.18	0.97	0.16
Number of vehicles per household member	0.88	0.43	0.84	0.40
Income less than $10,000	0.01	0.10	0.02	0.15
$10,000 to $19,999	0.02	0.12	0.04	0.20
$20,000 to $29,999	0.03	0.17	0.04	0.20
$30,000 to $39,999	0.05	0.22	0.03	0.18
$40,000 to $49,999	0.05	0.21	0.05	0.22
$50,000 to $59,999	0.09	0.28	0.05	0.22
$60,000 to $74,999	0.11	0.31	0.06	0.25
$75,000 to $99,999	0.22	0.41	0.28	0.45
$100,000 to $149,999	0.22	0.41	0.19	0.39
$150,000 or more	0.21	0.41	0.22	0.41
Log transformed trip distance	0.60	1.63	0.78	1.56
Rail transit access	1.00	0.00	0.00	0.00
Non-commuting purpose: number of trips in treated TAZs (n=2,474) and control TAZs (n=2,622)				
Walking trip (1=walk, 0=other modes)	0.11	0.31	0.09	0.29
Age	46.60	13.58	47.27	14.14
Gender (1=female, 0=male)	0.55	0.50	0.60	0.49
Hispanic (1=Hispanic, 0=non-Hispanic)	0.04	0.20	0.05	0.22
License ownership (1=yes, 0=no)	0.95	0.22	0.95	0.23
Number of vehicles per household member	0.83	0.48	0.82	0.41
Income less than $10,000	0.05	0.21	0.04	0.19
$10,000 to $19,999	0.06	0.23	0.04	0.21
$20,000 to $29,999	0.06	0.23	0.05	0.22
$30,000 to $39,999	0.06	0.24	0.06	0.24
$40,000 to $49,999	0.06	0.24	0.07	0.26
$50,000 to $59,999	0.06	0.24	0.04	0.21
$60,000 to $74,999	0.07	0.26	0.08	0.28
$75,000 to $99,999	0.19	0.39	0.17	0.38
$100,000 to $149,999	0.19	0.39	0.25	0.43
$150,000 or more	0.21	0.41	0.18	0.39
Log transformed trip distance	0.84	1.68	0.50	1.65
Rail transit access	1.00	0.00	0.00	0.00

Results from the multi-level logistic regression models indicate a strong association between sociodemographic, travel, rail transit access, and walking trips for commuting. Table 5 presents both fixed and random effects from three multi-level logistic regression models for commuting walking trips. Model 1, which includes only individual-level variables, shows that some sociodemographic characteristics of individual travelers are associated with walking trips for commuting purpose. Among various sociodemographic characteristics, having a driver's license and number of vehicles per household member are statistically significant. The odds ratios of having a driver's license (0.295) and number of vehicles per household member (0.478) indicate that they tend to lower the probability of commuting walking trips within TAZs.

Model 2 adds travel attributes as an explanatory variable in addition to the individual sociodemographic variables in model 1. The results of model 2 present the effect of travel characteristics on walking behavior. As expected, trip distance is negatively associated with walking trips for commuting by having the odds ratio of 0.184. In other words, longer trip distance reduces the likelihood of walking for commuting since the distance is strongly associated with the disutility of traveling. Therefore, trip-makers are likely to choose a faster mode than walking as the distance to destination increases. After adjusting for the travel attribute in the model, we find some changes in the influences of sociodemographic characteristics on walking trips for commuting purpose. In model 2, the association between number of vehicles per household member and commuting walking trips disappears while the influence of having a driver's license on commuting trips persists. Individuals with driver's license are 0.275 times less likely to walk for commuting purpose than those without driver's license. The households with incomes between \$10,000 to \$19,999 (income group 2) show a statistically significant odds ratio of 12.471. However, this association does not appear across all income categories.

Model 3 is our final model, which includes the presence of rail transit access as a key explanatory variable at TAZ-level in addition to sociodemographic and travel characteristics. The result of the log-likelihood test between the unrestricted model with rail transit access variable and the restricted model without the variable indicates that the unconstrained model, which is the final model, is better at the 99 percent confidence level. The results of model 3 show that the rail transit access variable is significant at a 95% confidence level after accounting for individual-level variables. The 2.504 odds ratio of rail transit access implies that the odds of choosing walking mode is 2.504 times larger in the treated TAZs compared to the control TAZs. That is, people are more likely to choose walking in areas with rail transit access compared to those in areas without rail transit access. When we translate the impact of rail transit access on the prevalence of walking into probability, it is much easier to understand the trend. The probability of choosing to walk in the treated TAZs is 7.4%, whereas that in the control TAZs is only 3.1%. Similar to the results from the previous two models, some sociodemographic characteristics exhibit distinct influences on walking trips for commuting in model 3 as well. Having a driver's license tends to lower the probability of walking trips for commuting purpose. The lower-income group is also significantly associated with commuting walking trips. However, these influences are less profound compared to those in the previous two models. In terms of travel attribute, we find that trip distance is the most critical determinant of walking behavior for commuting similar to the results of the second model.

Table 5. Multi-level logistic regression models for commuting walking trips

	Model 1 Sociodemographic characteristics		**Model 2** Sociodemographic and travel characteristics		**Model 3** Sociodemographic, travel, and rail access	
Variable	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**
Constant	0.624	0.688	1.147	1.488	0.796	1.053
Rail transit access					2.504 ***	0.766
Age	1.035	0.052	0.968	0.061	0.963	0.062
Age squared	0.999	0.001	1.000	0.001	1.000	0.001
Female	0.988	0.194	0.881	0.230	0.928	0.246
Hispanic	0.415	0.216	0.539	0.427	0.502	0.394
Driving license	0.295 ***	0.135	0.275 **	0.174	0.329 *	0.204
Vehicles per H.H. size	0.478 ***	0.128	0.705	0.242	0.680	0.235
Income group 1 (Reference)						
Income group 2	4.078 *	3.029	12.471 ***	11.754	12.501 ***	12.022
Income group 3	0.585	0.468	0.347	0.334	0.286	0.281
Income group 4	1.151	0.878	1.849	1.737	1.386	1.337
Income group 5	0.979	0.730	3.580	3.117	2.728	2.430
Income group 6	0.812	0.602	2.659	2.272	1.728	1.523
Income group 7	0.650	0.480	1.129	0.989	0.729	0.657
Income group 8	0.805	0.543	1.992	1.505	1.746	1.350
Income group 9	0.425	0.299	1.425	1.144	1.014	0.838
Income group 10	0.377	0.265	0.909	0.713	0.642	0.520
Trip distance (log)			0.184 ***	0.025	0.186 ***	0.025
N		1,340		1,340		1,340
Log(L)		-432.019		-221.571		-216.286
ρ^2 (market share model as base)		0.081		0.529		0.540
Adj. ρ^2 (market share model as base)		0.049		0.495		0.504

**Significant at 95%

Table 6 presents the multi-level logistic regression models of factors associated with non-commuting walking trips. Similar to model 1, the independent variables in model 4 are sociodemographic characteristics of the individual traveler. Model 4 for non-commuting trips presents more sociodemographic variables that are statistically significant than the models for commuting trips. The results reveal that attributes such as gender, ethnicity, having a driver's license, number of vehicles per household member, and income level show distinct influences on walking for non-commuting trips. The odds ratios of female (0.694), having a driver's license (0.230), and number of vehicles per household member (0.217) indicate that they are likely to lower the probability of walking trips for non-commuting related purposes. The odds ratio of the percent of Hispanic persons in the population suggests that Hispanic individuals are 2.605 times as likely to choose walking for non-commuting related trips than non-Hispanic individuals. While not all income groups are statistically significant, the level of income is negatively related to walking for non-commuting trips, indicating that a household with higher income except for income groups 2 and 4 is less likely to walk.

Similar to model 2, model 5 adds the travel attribute variable to sociodemographic variables. Model 5 presents the odds ratio of 0.184 for trip distance, indicating that the odds of choosing walking for non-commuting trips decreases by 0.184 for one unit increase in trip distance. After controlling for the travel attribute, the associations between sociodemographic characteristics and walking for non-commuting trips still exist. Age and percent of Hispanic persons in the population variables significantly predict walking trips for non-commuting purpose. In addition to these attributes, female, having a driver's license, and number of vehicles per household member are less likely to make walking trips for non-commuting purposes by presenting the odds ratios of 0.780, 0.163, and 0.303, respectively. Even though there is a statistically significant negative association between the level of income and non-commuting walking trips, this trend does not appear across all income groups.

Model 6 is our final model with rail transit access variable for non-commuting related trips. The results of model 6 present that all sociodemographic and travel characteristics are associated with walking for non-commuting trips. Model 6 also presents the statistical significance of rail transit access on the probability of choosing to walk for non-commuting trips after controlling for all other individual-level variables. The odds of choosing to walk for non-commuting related trips is 1.655 times higher in the treated TAZs compared to the control TAZs. It means that the treated TAZs show a high probability of choosing to walk (44.7%) compared to the control TAZs (32.8%). Since this trend persists in both commuting and non-commuting trips, we conclude that the "T" is a critical element in increasing walking trips for all purposes in TOD areas.

Table 6. Multi-level logistic regression models for non-commuting walking trips

	Model 4 Sociodemographic characteristics		**Model 5** Sociodemographic and travel characteristics		**Model 6** Sociodemographic, travel, and rail access	
Variable	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**
Constant	1.519	0.679	0.356 *	0.201	0.287 **	0.162
Rail transit access					1.655 ***	0.309
Age	1.021	0.020	1.071 ***	0.027	1.067 **	0.027
Age squared	1.000	0.000	0.999 ***	0.000	0.999 **	0.000
Female	0.694 ***	0.074	0.780 *	0.101	0.782 *	0.101
Hispanic	2.605 ***	0.518	2.822 ***	0.719	2.897 ***	0.733
Driving license	0.230 ***	0.044	0.163 ***	0.041	0.168 ***	0.042
Vehicles per H.H. size	0.217 ***	0.036	0.303 ***	0.061	0.303 ***	0.060
Income group 1 (Reference)						
Income group 2	0.652	0.173	0.648	0.231	0.659	0.233
Income group 3	0.437 ***	0.119	0.878	0.314	0.900	0.319
Income group 4	0.646	0.177	1.795	0.648	1.800	0.648
Income group 5	0.244 ***	0.075	0.440 *	0.185	0.452 *	0.190
Income group 6	0.334 ***	0.112	0.587	0.255	0.576	0.249
Income group 7	0.194 ***	0.065	0.401 **	0.163	0.414 **	0.168
Income group 8	0.283 ***	0.070	0.507 **	0.163	0.521 **	0.167
Income group 9	0.357 ***	0.088	0.677	0.221	0.709	0.231
Income group 10	0.504 ***	0.122	1.059	0.340	1.075	0.343
Trip distance (log)			0.295 ***	0.016	0.295 ***	0.016
N	5,096		5,096		5,096	
Log(L)	-1399.63		-944.03		-940.45	
ρ^2 (market share model as base)	0.133		0.415		0.418	
Adj. ρ^2 (market share model as base)	0.124		0.406		0.407	

**Significant at 95%

5 Discussion and conclusion

This study revisits Chatman's (2013) question: "Does TOD need the T?" by addressing the role of transit access in influencing walking behavior in TOD areas. In the existing literature, high density, mixed land use, pedestrian-friendly environments, and quality public transit facilities and service are major components of TODs in promoting active modes of transport. Among these various attributes of TOD, we particularly evaluated the role of rail transit access on walking trips that are generated from TOD areas. To estimate the true effect of transit access on walking trips, we first identified the treated TAZs and control TAZs that have similar built environment characteristics using the PSM technique. The only difference between the treated and control TAZ groups is the presence of rail transit access. We then compared walking trips for commuting and non-commuting purposes between the two TAZ groups by employing multi-level logistic regression models. Since TOD areas typically generate more walking trips to transit stations compared to non-TOD areas, we excluded any walking trips that are related to transit use. This unique research design provided an opportunity to reduce bias in samples and examine walking behavior in the Atlanta metropolitan area.

The major finding from this study is that the presence of rail transit access does have a measurable association with walking trips for all purposes that do not involve transit use after controlling for sociodemographic and travel characteristics. In other words, "T" is a critical element in TOD. Two theoretical propositions—behavioral spillover effects and social interaction effects—can explain the prevalence of walking that is not relevant to transit use in TOD areas. Based on the behavioral spillover theory, the adoption of one behavior leads to the additional adoption of related behaviors. Since there is a relatively large number of people who walk to and from transit stations in TOD areas, their behavior may lead to more walking trips to other destinations than transit stations. These additional walking trips can be linked to a trip chain to and from transit stops or an individual trip. According to the social interaction theory, people within the same group are likely to behave similarly. This implies that people's propensity to walk would increase when there is a high volume of pedestrians in TOD areas.

The research finding also supports current policies that target compact and dense urban forms around transit facilities to promote sustainable transportation to destinations other than the transit stops. Currently, the U.S. Department of Transportation's Federal Transit Administration (FTA) is offering supportive programs and technical assistance to localities to advance sustainable modes of travel. FTA has funded about 20 transit organizations across the country to support their TOD projects to improve public transit access, and the amount of funding has increased from $14.7 million in 2016 to $19.2 million in 2019 (FTA, 2019). Our finding of the positive association between TODs and walking behavior for both commuting and non-commuting purposes supports the soundness of such investments. Well-planned TODs have successfully served neighborhoods by connecting transit to surrounding places with diverse amenities such as jobs, housing, retail, restaurants, open spaces, and pedestrian-friendly environments. The results of this study indicate that TODs may have also helped in improving overall walkability, which benefits the environment and supports a healthy lifestyle.

Our findings indicate an important relationship between transit access and walking behavior; however, this study has some limitations. First, the main threat to this study is self-selection bias occurring when individuals who like to walk choose to live in TOD areas. Because our analytical models did not control for residential self-selection due to the data structure, the estimated treatment effect might be overestimated if there are strong residential and travel-related preferences in the study area. A longitudinal research design or a model that controls for individuals' travel-related preference may be helpful to deal with the self-selection issue.

Second, previous studies noted that people are less likely to own a vehicle and have a driver's license when they live in transit-accessible areas (Ewing & Hamidi, 2014). The limited access to an automobile because of higher transit access may have both direct and indirect effects on walking trips. However, this study is limited to estimating only the direct effect on walking trips. This fact may lead to the underestimation of rail transit's contribution to our study. Future studies can employ path analysis, structural equation modeling, or other adequate models to address this limitation.

Third, this study did not differentiate TOD types in the model specification. Considering that transit agencies have developed TODs for different goals based on where they are located, analyzing the effects of TODs using separate models for urban and suburban areas may provide useful insights in improving TOD plans and guidelines, particularly TODs which aim to support broader transit networks that cover both urban and suburban areas. Unfortunately, we found that most TAZs in our study area are categorized as urban TAZs. Thus, a future study may need to expand the geographical scope, which covers multiple metropolitan regions.

Fourth, this study only evaluated the influence of origins on walking trips. Recent studies have noted that destination and route attributes are also associated with walking behavior (Moran, Rodríguez, & Corburn, 2018; Vale & Pereira, 2016). The model specifications that consider built environmental attributes of both origins and destinations may provide more concrete results. In addition, this study may need additional variables in terms of omitted variables such as parking prices and availability and crime that may also be associated with walking trips. However, given prior studies, the omission of crime and parking variables might suggest that our estimates for walking in TOD areas are conservative.

Finally, this study did not investigate the impact of individual built environment variables on walking behavior. Since the main objective of this study was to examine whether increased walking is related to the presence of rail transit independent of built environment characteristics, PSM used the presence of rail as a key differentiator between treated and control groups. Even if PSM finds two comparable TAZ groups that share similar built environment characteristics except for rail transit, there may still be differences in built environment variables between the two groups. Thus, further research is required to test all built environment variables one-by-one by including them in the regression models and examine whether any of them appears to have a significant effect on walking.

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