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Full Random Coefficients Multilevel Modeling of the Relationship between Land Use and Trip Time on Weekdays and Weekends

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Abstract: Interests in weekend trips are increasing, but few have studied how they are affected by land use. In this study, we analyze the relationship between compact land use characteristics and trip time in Seoul, Korea by comparing two research models, each of which uses the weekday and weekend data of the same travelers. To secure sufficient numbers of subjects and groups, full random coefficients multilevel models define the trip as level one and the neighborhood as level two, and find that level-two land use characteristics account for less variation in trip time than level-one individual characteristics. At level one, weekday trip time is found to be reduced by the choice of the automobile as a travel mode, but not by its ownership per se. In addition, it becomes reduced if made by high income travelers and extended to travel to quality jobs. Among four land use characteristics at level two, population density, road connectivity, and subway availability are shown to be significant in the weekday model. Only subway availability has a positive relationship with trip time and this finding is consistent with the level-one result that the choice of automobile alternatives increases trip time. The other land use characteristic, land use balance, turns out to be a single significant land use variable in the weekend model, implying that it is concerned mainly with non-work, non-mandatory travel.

Keywords: land use; trip time; sustainability; multilevel modeling; Seoul

1. Introduction

Weekend trips are less structured and, usually, quite distinct from weekday trips [1]. They are distinct especially in travel purposes (mostly non-mandatory purposes of travel, such as tourism, shopping, social affairs, leisure, and recreation), travel modes (large share of automobile trips), peak hours (high flexibility of the departure and arrival time and subsequent wide range and less clarity of the peak hours), destinations (high variation and substitutability), and trip length (often extended length) [2]. However, partially due to the traditional importance of weekday commute trips, weekend trips have been underrepresented in transportation policies and plans [3]. In the same sense, travel data have been collected with regard mainly to weekday trips, and it explains why theoretical and empirical studies on weekend trips are few [1,4,5]. This in turn made transportation policies and plans overly depend on the findings of weekday trip studies [2]. Meanwhile, such a lack of weekend trip studies is somewhat attributed to the unstructuredness of non-mandatory weekend trips [6] or high variation of their temporal and spatial distributions [5]. That is, because of low predictability, studies without significant findings may not have been properly published [7].

However, weekend trips are increasing, and they are in even greater need of empirical research [2]. Nonetheless, beginning from a description of travel patterns by day of the week, the transportation literature has inferentially analyzed differences between weekday and weekend trips (e.g., [8]).

However, studies on how weekend trips respond to land use variations are still few. Thus, to gain a fuller understanding of the land use–travel relationship, a study on the land use effect on weekend trips in comparison to weekday trips is warranted [9].

This study, using Seoul, Korea as a case study, aims to analyze differences in weekday and weekend trips in relationship to land use. Trips are evaluated with trip time. The length and time spent for a trip is directly connected with the efficiency of road systems and their environmental impact, and at the city level, it has been widely adopted as an important indicator for sustainable transportation [10]. In addition, at the individual level, trip time is an indicator of the quality of life, a component of sustainability, in the sense that mobility allows individuals to conduct maintenance, social, and economic activities [10]. Especially regarding compact land use, it has been reported to barely work on the reduction of the trip frequency, but rather on that of the total travel distance/time [11]. This implies that compact land use mainly reduces trip length/time. The reduction is brought about by a shorter physical distance/time between the origin and destination of a trip [12] through, for example, better trip-chaining and destination localization [11]. (Compared to trip length, trip time—a travel indicator for this study—reflects the fact that compact development also increases road congestion. Indeed, trip length is meaningful by itself, but was not considered in this study due to data limitations. In particular, while this study uses the Capital Region Travel Survey (CRTS), the survey asked respondents to record their trip origin and destination on the scale of the neighborhood instead of the exact addresses.) Due to reductions in trip length and time, individuals have become less dependent on automobiles [13] and more reliant on alternatives, such as walking, bicycles, and public transit, which accordingly reduces automobile driving, and, even though people keep using automobiles, the driving distance is shortened per se [13].

This study expands previous research on the land use–travel relationship for weekday and weekend travel. It employs multilevel (hierarchical linear) modeling to correct for estimation error (non-independence and heteroscedasticity issues of the OLS regression model), which is present when variables in different units of observation are analyzed together in one model. Notably, this study advances a multilevel model that has been used in previous studies on the land use–travel relationship. Particularly, instead of the random intercepts model, it employs the full random coefficients model, which best reflects reality [14] by allowing for the random variation not only in intercepts, but also in coefficients/slopes by group/area (to be discussed later).

2. Empirical Relationship between Land Use and Weekend Travel

Before empirical studies began to analyze the relationship between land use and weekend trips, the relationship has been suspected by expanding the findings of those studies that examined weekday trips. One well-known suspicion is the compensatory travel hypothesis: The urban spatial structure designed for the reduction of trip length/time on normal days (i.e., for the encouragement of internal trips and subsequent non-motorized trips) limits access to green spaces, and it causes a balloon effect on weekends; that is, as a compensation for the limited access, weekend trip length/time becomes larger (through the facilitation of external trips and subsequent motorized trips). However, empirical studies have found that such a balloon effect is not significant [15] or, contrary to the hypothesis, suburban residents who travel long distances for weekday commute also have longer distances for leisure travel [16].

Regarding weekend trip research, basic descriptive analyses continued until the 1990s. For example, Hu [17] simply described trip patterns by day of the week and Murakami [18] illustrated how weekend trips differ by purpose, mode, and household size. As a study that considered land use, Rutherford et al. [19] presented with crosstabs and graphs variations in weekend unit trip length and total travel distance among a few key areas that represent different land uses.

Inferential research on weekend trips began in the early 2000s and it can be categorized into three types as shown in Table 1: (1) separate analysis for weekend trips; (2) single model studies that incorporated both weekday and weekend data; and (3) use of multi-trip data that separated weekday and weekend trips.

Table 1. Inferential research on the land use–weekend travel relationship.

Authors	Years	Data	Methods	Results
Lanzendorf	2002	*Weekend data*: two-weekend-day survey in four neighborhoods in Cologne, Germany	Binomial logistic regression and multiple linear regression	Urban form variables such as residential neighborhood and garden ownership affect automobile use for weekend leisure travel.
Bhat and Gossen	2004	*Weekend data*: weekend subsample of the 2000 BATS (Bay Area Travel Survey)	Mixed multinomial logistic regression	Land use balance and density do not differentiate weekend recreation trips.
Bhat and Srinivasan	2005	*Weekend data*: weekend subsample of the 2000 BATS	Mixed ordered-response logistic regression	Land use balance and density do not affect weekend non-work trips.
Troped et al.	2000	*Weekday and weekend data*: accelerometer and GPS records for four consecutive days (including two weekend days) in Massachusetts	*One model without a weekday–weekend difference dummy*: multiple linear regression	Population and housing density, land use balance, and intersection density positively affect physical activity levels.
Forsyth et al.	2007	*Weekday and weekend data*: travel diary and accelerometer records for one week in Twin Cities, Minnesota	*One model without a weekday–weekend difference dummy*: *t*-test	Residential density has a modest association with walking and physical activity.
Cervero and Duncan	2003	*Weekday and weekend data*: entire 2000 BATS data (two days = one weekday + one weekend day)	*One model with a weekday–weekend difference dummy*: binomial logistic regression	Land use diversity and design factors exert a very week effect on walking and biking choices.
Ogilvie et al.	2008	*Weekday and weekend data*: a survey in deprived neighborhoods in Glasgow, Scotland	*One model with a weekday–weekend difference dummy*: multinomial logistic regression	Except for local destination access, environmental variables generally have a limited effect on active travel and physical activity.
Lin and Yu	2011	*Weekday and weekend data*: a survey of students at three elementary schools in Taipei, Taiwan	*Weekday–weekend separate models*: negative binomial regression and multinomial logistic regression	Among residential land use variables, land use mix has a significant effect on leisure trips and intersection and building densities on transit and non-motorized trips.
Written et al.	2012	*Weekday and weekend data*: survey and seven-day accelerometer records in 48 neighborhoods in New Zealand	*Weekday–weekend separate models*: multiple linear regression	In relation to the leisure-time physical activity, destination accessibility, street connectivity, and residential density are significant both in the weekday and weekend models (the other two variables, land use mix and streetscape quality, are insignificant).
Lee et al.	2009	*Weekday and weekend data*: SMARTRAQ (Strategies for Metropolitan Atlanta's Regional Transportation and Air Quality) household travel survey	*Weekday–weekend separate models*: Tobit models	Regarding the total travel time (not just leisure travel time), its reduction is associated with housing and commercial district densities and rail proximity in the weekday model, whereas no variables are significant in the weekend model.

As the first type of inferential research, almost all travel studies that are based only on weekend data were actually done to evaluate leisure trips whose proportion is overwhelming on weekends. Lanzendorf [20] conducted a survey for the two weekend days in four neighborhoods in Cologne, Germany for the purpose of analyzing variations in leisure trips according to mobility styles (attitudes to mobility). Similarly, Bhat and Gossen [1] and Bhat and Srinivasan [21] selected a weekend sample from the 2000 Bay Area Travel Survey (BATS) data to analyze how land use differentiates leisure activities.

The second type of studies used a single model to analyze weekday and weekend trips together. These studies can be further categorized into cases that controlled for the weekday–weekend difference using a dummy covariate and others that did not consider such a statistical control. First, among studies without the control, Troped et al. [22] analyzed accelerometer records as measured for four consecutive days (including the two weekend days) for the purpose of testing the relationship between land use and physical activities. Forsyth et al. [3] collected data from travel diaries and accelerometers for a one-week period and investigated how variations in walking and physical activities are affected by residential density. Second, Cervero and Duncan [23] is among those that analyzed multi-day trip data and at the same time, used a binary covariate to account for the weekday–weekend difference. In addition, unlike above-stated Bhat and Gossen [1] and Bhat and Srinivasan [21] who selected the one-day weekend sample of the 2000 BATS data, Cervero and Duncan [23] used the entire data of one weekday and one weekend trips and in a binomial logistic regression model of the mode choice (walk versus bike), they included a variable of the trip-generation day in addition to other trip characteristic dummies. Likewise, Ogilvie et al. [24] analyzed whether along with individual and environmental variables, a dummy of the survey day difference (weekday or weekend) is associated with variations in active trips and physical activities.

A relative weakness of such studies is the inability to discern weekday–weekend trip variations. In regard to external validity, however, their findings may be applicable to both of weekday and weekend trips. This is an improvement from those that analyzed either weekday or weekend data alone. Meanwhile, although studies with the dummy may be preferable, they do not test which explanatory variables lead to the trip variations (i.e., if the dummy variable is significant, only the intercept changes while all coefficients stay the same).

By contrast, the last, third type of studies separately specified weekday and weekend models by dividing trip data and compared the results of the respective models; this particular study falls into this type. Lin and Yu [25] separated weekday and weekend trip data to analyze the relationship between land use of residential areas and leisure trips that were made by students at three elementary schools in Taipei. As a result of negative binomial regression, street intersection density was found to have a negative effect on trip generation no matter when it is made on weekdays or weekends. Written et al. [26] investigated in 48 New Zealand neighborhoods the relationship between land use and leisure time physical activities and particularly, they analyzed whether the relationship is differentiated according to whether the activities are measured as perceived by a survey tool or objectively by an accelerometer. In the case of the accelerometer measurement, data were collected for seven consecutive days and analyzed in separate weekday and weekend regression models. The two models consistently found that physical activities are significantly associated with destination accessibility, road connectivity, and residential density, but not with land use mix and streetscape quality. Lee et al. [8] separated the data of SMARTRAQ (Strategies for Metropolitan Atlanta's Regional Transportation and Air Quality) into weekday and weekend samples and analyzed household travel through separate Tobit models. (Their study is similar with this particular study, in the sense that different, from Lin and Yu [25] and Written et al. [26], they did not pull out only leisure trips, but analyzed all purposes of trips together.) As a result, they found that different variables are concerned with travel time variations: in he weekday model, household and commercial district densities and rail proximity and none in the weekend model. (By contrast, in those studies by Lin and Yu [25] and by Written et al. [26], both of which used leisure trip data only, significant variables were reported to be the same in weekday and weekend models.) A limitation of the study is that two different samples were used for the weekday and weekend models, so it is hard to identify among the total, observed difference in the results of the two models, which proportion is brought about by the weekday–weekend difference, not by the sample difference. (In comparison, this particular study uses the same sample for its weekday and weekend models.) Besides, as a common difference from previous studies that employed separate weekday and weekend models, including the above study by Lee et al. [8], this study uses multilevel modeling to relax the independence and homoscedasticity assumptions that are violated by including in the same model those variables at different levels of observation and thus, to draw more accurate estimates: The risk of Type I (false positive) error is reduced.

Indeed, with its benefit in relieving the assumptions of homoscedasticity and independence, travel studies have employed multilevel modeling since the early 2000s (e.g., [27–31]). However, from these examples to a recent study in 2011 by Antipova, Wang, and Wilmot [32], the research focus was on commute trips. In 2014, studies began to apply multilevel modeling to all daily trips regardless of travel purpose [33] or to business and non-business trips together [34]. However, these two studies did not consider weekend trips: Clark et al. [33] used one-weekday data and Hong et al. [34]—and the preceding study by Zhang et al. [35]—used the data of the PSTP, which represents two weekdays. As acknowledged by Clark et al. [33], with only weekday data, one cannot fully take advantage of the benefits of multilevel modeling in accurately estimating travel patterns and thus, a study is called for to examine the data of both weekday and weekend trips. This study addresses these shortcomings.

3. Multilevel Modeling

As for research on the relationship between land use and trips, a methodological issue is that the two concepts are measured at different levels/units. Land use is evaluated at certain areal units (e.g., census tracts and ZIP code areas), but trips are generated at the individual level. Regarding such an inconsistency in the units of observation, earlier studies often chose a spatial unit as the basic unit of analysis [4]. In these studies, travelers' individual characteristics (about sociodemographics and households as well as about trips) were aggregated to the spatial unit (e.g., median income and proportion of a particular age group). However, this aggregation ignores variations within the spatial unit, and leads to the ecological fallacy [4]. Therefore, disaggregate studies at the individual level are considered more appropriate [4,29]. Currently, most empirical studies define the individual as the unit of analysis according to which all individuals within the same spatial unit (unit of observation for land use variables) are inherently assumed to be exposed to the same land use [4].

However, this assumption firstly results in heteroscedasticity—or *spatial heterogeneity*, meaning that the independent–dependent variable relationship varies according to the spatial context—and subsequently increases the chance of Type I error: Because of the fact that one level is nested within another, estimated standard errors are deflated/biased and thus, regression coefficients are erroneously estimated to be significant (i.e., atomistic fallacy). Indeed, Hong et al. [34] analyzed the land use–travel relationship through OLS regression and multilevel modeling and presented that the effects of land use variables tend to be more significant by OLS estimation: Among land use variables, land use entropy and street intersection density were significant in the OLS model, but not in the multilevel model. Regarding this heteroscedasticity, multilevel modeling relieves the homoscedasticity assumption by assigning individual travelers to be nested/clustered within neighborhoods: In particular, it separates neighborhood-level effects from individual-level effects by specifying and estimating two levels of variances, between-individual variance and between-group variance.

When the land use–travel relationship is inferred at the disaggregate level, a second issue is *spatial autocorrelation* [34]. It occurs when certain unobserved characteristics (e.g., attitudes to automobile trips) that are shared by individuals in the same spatial unit make the individuals have similar values (i.e., homogeneity and mutual dependence): Because of the unobserved variables that are missing in a statistical model, the assumption of independence of individuals/observations is violated. To deal with this spatial autocorrelation, multilevel modeling estimates coefficients differently by group.

Indeed, in the transportation literature, Bottai et al. [36] and Mercado and Páez [10] highlighted the need for multilevel modeling considering the mutual dependence and contextual effect on travel behavior in a cluster. The contextual effect, also called the place/neighborhood effect, refers to the influence that variations in place or group characteristics (i.e., group-level variables) have on their constituents [37]: This contextual effect generates inter-group differences in an outcome. In this vein, while a place, an upper level in multilevel modeling, should be defined in the unit in which place characteristics affect individuals, the issue of incorrect grouping has been discussed in travel behavior studies (e.g., [38,39]) (to be discussed).

Multilevel modeling comprises a fixed and a random part. The fixed part presents a systematic relationship with the intercept and/or regression/slope coefficients. Through extension of the random part, multilevel modeling handles the violation of the independence and homoscedasticity assumptions, according to the nesting of level-one individuals at level two. Therefore, a major difference between multilevel modeling and OLS regression lies in the random part, that is, whether variation around the fixed part is allowed for.

Whether the random part is limited to the intercept or applied to both of the intercept and coefficients determines the complexity of a model (and accordingly, the level to which the model reflects the reality). In fact, the random intercepts model is the most frequently used type of multilevel model [37], and it is particularly so among studies on the land use–travel relationship [27–29,32]. From the above-stated studies in the early 2000s [27–31] to recent studies by Mercado and Páez [10], Zhang et al. [35], Clark et al. [33], and Hong et al. [34], all these multilevel modeling studies used the random intercepts model or its equivalents. This is largely because model fit did not improve significantly, and studies could not proceed to the random coefficients model [28]. Meanwhile, taking a step further from the random coefficients model, this study selects the *full random coefficients model*, the most realistic type of multilevel model. Quite a few recent studies [40–42] argued that the assumption of the random intercepts model—regional differences bring about variations in the intercept while forcing those in the independent–dependent variable relationship to be fixed—lacks conceptual, intuitive credibility and, in this vein, they recommended that the random coefficients model should be used in any case.

For the detection of random coefficients, specifying all level-one variables at the same time is not desirable because the simultaneous estimation of the covariances of the variables is too complex (or an additional random coefficient, the number of random parameters to be estimated dramatically increases in the order of 1, 3, 6, 10, and 15 and, thus, five random coefficients indicate excessive computational complexity for statistical software to handle)and it also increases potential for parameter overestimation. Moreover, due to an excessive number of random coefficients, the model itself may not converge. Thus, random coefficients should be added one by one.

To identify variables whose coefficients exert random effects, researchers may run the χ^2 difference test to check if the predictive power of the model is significantly improved. If so, they can add the very variable if it is also significant [43]. (Meanwhile, beginning with a study by Barr et al. [40], two conflicting arguments continue. A group of studies (e.g., [41,42]) argued that studies should always use the maximum number of random coefficients (because random coefficients models are theoretically superior) except the case that solutions are not found or computations are too complex. However, others (e.g., [44]) reported that, based on real data, not simulation, a parsimonious model—where the number of random coefficients is adjusted—is preferred).

Up to the random coefficients model, a multilevel model is typically built stepwise. The beginning is the estimation of the null model. Without independent variables, it has only two random terms for the two levels of analysis. Then, researchers move to the random intercepts model by including level-one variables and subsequently level-two variables. Lastly, by specifying random effects to level-one variables, the (full) random coefficients model is completed.

To justify the two-level specification, the level-two variance (random term) of the null model should be significantly greater than zero. It then confirms that individuals are clustered within neighborhoods. Another criterion that is calculated from the variance estimates in the null model is the intraclass correlation coefficient (ICC). It is defined as among the total variance, the proportion of variance explained by the upper level. In general, multilevel models in behavioral studies have the ICC of 5–25% and if it is less than 5%, simpler OLS regression may be preferred [37]. This study satisfies this 5% criterion (to be shown). (Actually, this rule-of-thumb is still a topic of debate [45]. For example, Lee [46] recommended that the ICC should be above 10% by arguing that, if not, the nesting effect is negligible. As another criterion, Sorra and Dyer [47] reported that the ICC of higher than 5% suggests that the between-group variance is greater than expected by chance. In contrast, according to Nezlek [48], even though the ICC is close to zero, multilevel modeling should be adopted if the independent–dependent variable relationship is considered to vary across groups because otherwise, researchers implicitly accept the assumption that the relationship is consistent across the groups. McCoach and Adelson [49] also argued that although the ICC is 5% or less, multilevel modeling needs to be employed in order to prevent the risk of underestimating standard errors. Including the above-stated studies by Lee [46] and McCoach and Adelson [49], Adelson and Owen [50] reviewed previous studies on multilevel modeling and concluded that multilevel modeling is appropriate in the ICC range of 5–10% or above. Thus, up to this point, the minimum ICC of 5%, as suggested by Sorra and Dyer [47] and Lee and Noh [37], appears to justify complex computation by multilevel modeling).

The last consideration is the sample size for which varying rules-of-thumb have been proposed (see [37,45]). To have sufficiently large numbers of subjects and groups, this study specified the trip at level one and the neighborhood at level two. Notably, for sufficient power, the number of groups should be taken into account more critically than the number of observations [45]. At the group level, the sample size of a minimum of 20 neighborhoods is generally acceptable, but if upper-level variables are crucial to the structural model (as with land use variables of this study), the size should be more than 100 [51]. This indeed indicates that while earlier multilevel modeling studies on travel behavior carefully selected a small number of neighborhoods with different land use patterns, the selection itself may have caused the issue of the group-level sample size. By comparison, the data of this study were formatted to be appropriate for testing the significance of land use variables (i.e., n > 100); number of neighborhoods in the sample = 507. Another criterion is that multilevel models need 10–20 subjects per variable [45]. This study also meets this criterion; it can carry a maximum of 259–518 variables for the weekday model (based on 5179 trips) and 378–755 for the weekend model (according to 7551 trips), both of which actually include 31 variables at the first and second levels combined. In fact, regarding the subject-to-variable ratio, the criterion is more critical at the group level [45]. Then, while in theory, 507 neighborhoods allow 25–51 variables at level two, this study has only four level-two land use variables.

4. Data

Of the two concepts of the land use–travel relationship, this study evaluated *compact land use in the neighborhood of the traveler* with population density, land use balance, road connectivity, and subway availability. The latter four was measured within the 0.5-mile straight-line buffer from the boundary of the neighborhood and population density was defined as registered population per mi^2 in the neighborhood (according to the format of the population data). First, subway availability and road connectivity were evaluated by calculating the number of metro stations and that of street intersections, respectively, in the buffered area. The other land use variable, land use balance, was represented by Shannon entropy: $-1 \times \{[(Pa \div P) \times \ln(Pa \div P)] + [(Pb \div P) \times \ln(Pb \div P)] + [(Pc \div P) \times \ln(Pc \div P)] + [(Pd \div P) \times \ln(Pd \div P)]\} \div \ln(m)$, where Px = areal proportion of the x-th land use (x = housing, office, shopping, or leisure), m = total number of land uses, and P = total area of the land uses. This study evaluated all of the four land use variables using public data (see Table 2): (1) neighborhood population numerical data for population density; (2) land characteristics GIS polygon map for land use balance; (3) street centerlines GIS polyline map for road connectivity; and (4) metro stations GIS polygon map for subway availability.

Table 2. Research variables.

Variables: Sources (Dates)	Definitions/Units	Mean	S.D.	
Group Level				
Population density: Ministry of the Interior (31 December 2006)	Persons/mi^2	60,776.341	34,905.569	
Land use balance: The Seoul Institute (2007)	Shannon entropy (0–1)	0.632	0.174	
Road connectivity: Highway Management System (2007)	Street intersection points/mi^2	888.368	516.713	
Subway availability: New Address System (2007)	Subway station points/mi^2	1.549	1.002	
Individual Level *				
Weekday trip time	Minutes	37.281	31.499	
Weekend trip time	Minutes	45.229	45.603	
Birth year	Year	1969.486	16.141	
Household size	Household members	3.799	0.990	
Children	Household members under six	0.115	0.373	
Automobiles	Sedans + vans + trucks + taxis + motorbikes + others	1.026	0.631	
Sedans/vans	Sedans + vans	0.856	0.578	
	Categories	**Freq. (%)**	**Categories**	**Freq. (%)**
Intra-neighborhood trip	Yes	4198 (81.0)	No	982 (19.0)
Intra-district trip	Yes	2839 (54.8)	No	2341 (45.2)
Alternative-mode trip	Yes (trip not by automobile as driver + as passenger)	1282 (24.7)	No	3898 (75.3)
Job	(1) Student	1309 (25.5)	(2) Homemaker/unemployed/under school age	883 (17.2)
	(3) Professional/engineer	630 (12.3)	(4) Admin/office/manager	761 (14.8)
	(5) Sales	266 (5.2)	(6) Customer service	329 (6.4)
	(7) Agriculture/fisheries + manufacturing/transportation/general labor †	253 (4.9)	(8) Others	706 (13.7)
Housing type	(1) Condominium	2192 (42.3)	(2) Row house	689 (13.3)
	(3) Multi-family house	985 (19.0)	(4) Single-family house	1150 (22.2)
	(5) Officetel + others †	164 (3.2)		
Home ownership	(1) Ownership	3934 (75.9)	(2) *Jeonse* (two-year lease)	923 (17.8)
	(3) Tenancy	206 (4.0)	(4) Others	117 (2.3)
Income	(1) <1 million won	291 (5.7)	(2) 1–2 million won	1288 (25.1)
	(3) 2–3 million won	1381 (26.9)	(4) 3–5 million won	1791 (34.9)
	(5) 5–10 million won	328 (6.4)	(6) ≥10 million won	56 (1.1)

* All individual-level variables were measured using the data of the 2006 Capital Region Travel Survey (dates: 26 and 28–29 October 2006).† Two categories were combined.

Other than the above land use variables, this study measured research variables using the Seoul subsample of the data of the 2006 Capital Region Travel Survey (CRTS). First, consistent with land use, which was evaluated in the residential neighborhood, this study counted trips, the unit of analysis, only if they were generated at the residence. Variables that this study used to stand for trip characteristics include intra-/inter-neighborhood trip, intra-/inter-district trip, and automobile/alternative-mode trip. Other variables that were measured with the CRTS-Seoul subsample include the characteristics of the individual traveler (birth year and nine job categories) and of the household (household size, children, automobiles (all types), sedans/vans, six housing types, four home ownership types, and six income ranges) (All data used for this study are available upon request.) While travel behavior studies often reported these variables to be significant [52–55]—for example, automobile ownership has been used to explain commuting trip time [28,29,56,57]—housing ownership and type variables are somewhat particular to Korean studies on weekday and weekend travel [58–60]. (Actually, earlier U.S. studies also analyzed housing ownership [61] and types [61–63].) In Korea, housing types are widely considered to be linked to destination accessibility [59] and mobility (as with household income) [58]. By comparison, housing ownership has been discussed mainly in relation to mobility [58].

Compared to the initial 1996 and second 2002 surveys, the 2006 CRTS conducted along with the main weekday survey (3% of the total households in Seoul) on 26 October (as provided by law, the last Thursday of October), the supplementary weekend survey (5% of the weekday survey sample) on 28–29 October (the very following Saturday and Sunday). In addition, different from the later 2011 and 2016 surveys, the 2006 CRTS assigned a respondent the same ID for the weekday and weekend surveys. Thus, this study was capable of constructing the same sample for the weekday and weekend trip models (by extracting from the weekday survey sample only those who responded to the weekend survey) and directly comparing the results of the models (i.e., it controlled for differences in the results according to those between the samples).

Figures 1–3 shows neighborhood-scale distributions of 5179 weekday and 7551 weekend trips—as generated by 2364 Seoul residents—and their mean trip times (raw and log-transformed). The overall mean trip time was 37.28056 min on weekdays [mean of ln(trip time) = 3.33573] and 45.22865 on weekends [mean of ln(trip time) = 3.47849]. The higher means of the weekend trip frequency and time over their weekday counterparts well reflect the trip patterns of Seoul residents [2]. However, as in Tables 3 and 4, when all research variables are controlled for, the intercepts indicate that the *average* Seoul resident's trip times would be 44.48135 min on weekdays [=exp(3.79507)] and 46.96004 on weekends [=exp(3.84930)] if they have the mean age as well as the mean numbers of household members, children, and automobiles *across their neighborhood* (this study used group mean centering, and the intercepts have these specific meanings). The difference between the intercepts became modest, which suggests that the observed trip time difference was well accounted/controlled for by research variables in the models.

Lastly, in Figures 2 and 3, neighborhood-scale mean trip times have somewhat similar spatial patterns between weekdays and weekends. Pearson's correlation is weak, but significant [r = 0.255 (p = 0.000)] based on the log-transformation [with the raw variables, r = 0.078 (p = 0.082)]. Thus, one could argue that neighborhoods with longer means of weekday trip times are also likely to present longer weekend trips on average, and this supports LaMondia and Bhat's finding [16] that rejects the hypothesis of compensatory travel (see "Empirical Relationship between Land Use and Weekend Travel"). Nevertheless, in the sense that the unit of analysis is the neighborhood, not the individual trip, this argument carries the risk of the ecological fallacy as discussed above.

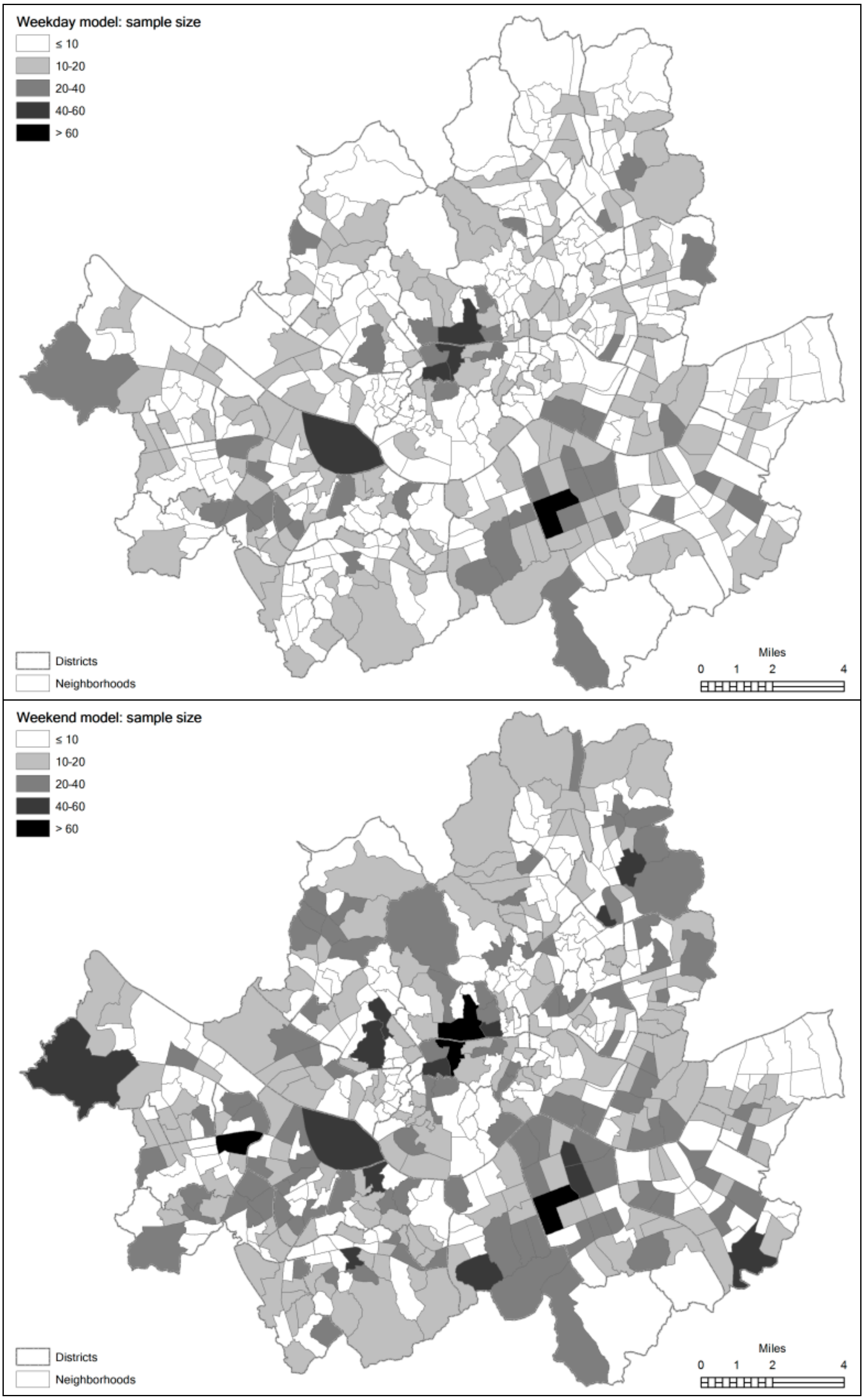

Figure 1. Weekday and weekend trips: sample sizes.

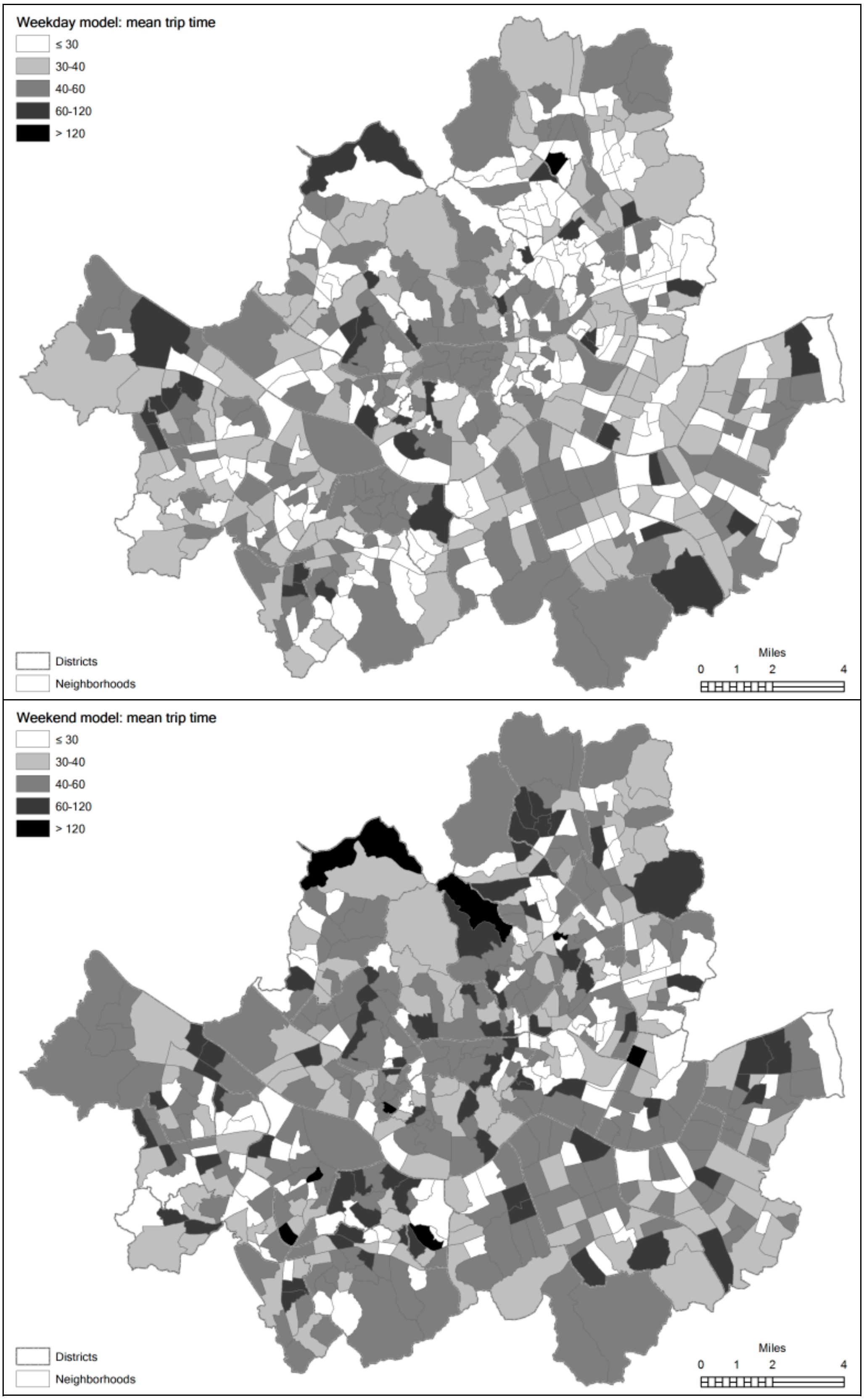

Figure 2. Weekday and weekend trips: mean trip times.

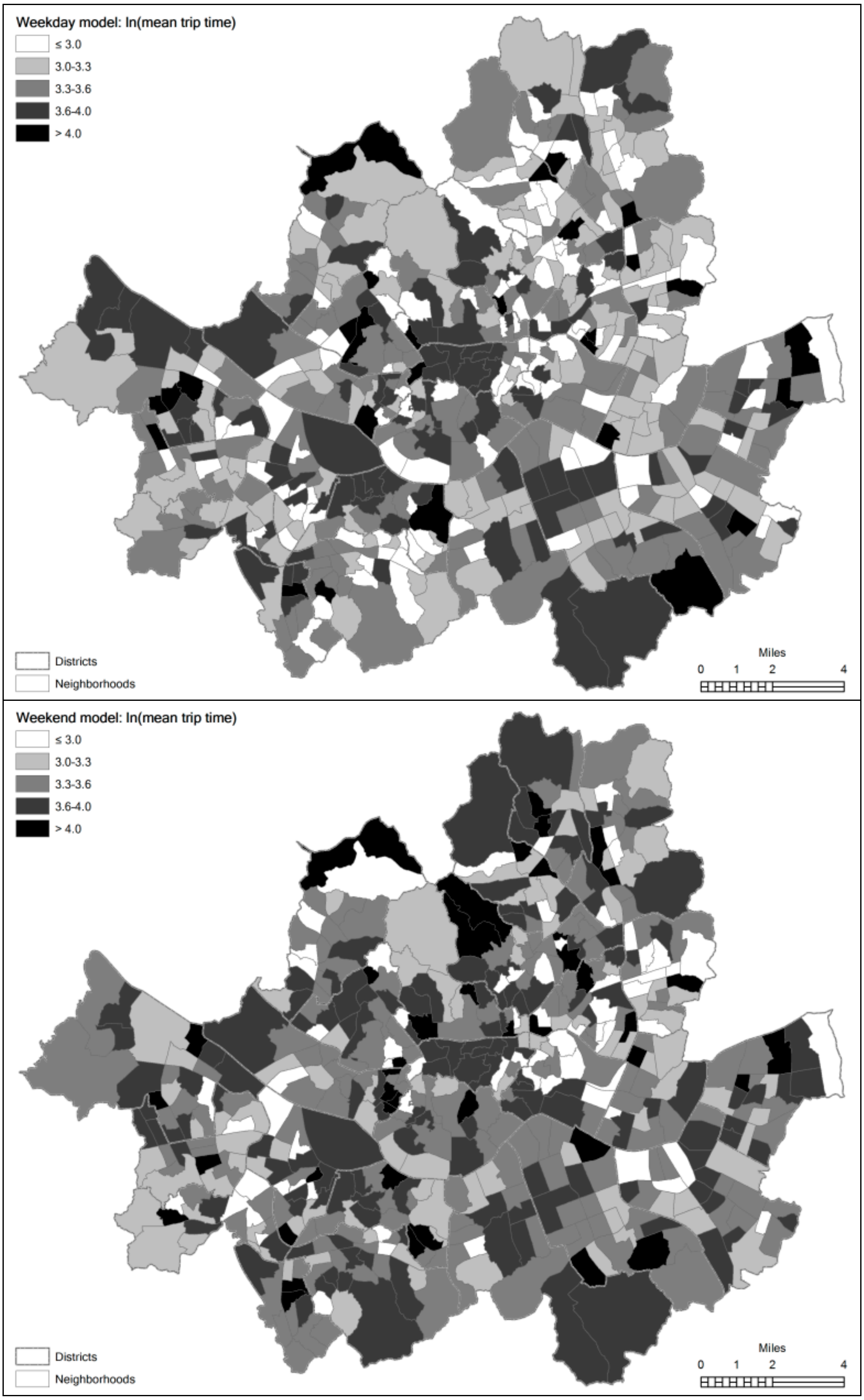

Figure 3. Weekday and weekend trips: log mean trip times.

Table 3. Multilevel modeling of log trip time (LnTTime) on weekdays (n = 5179 trips).

			Null Model		Random Intercepts Model (Including Only Level-1 Variables)		Random Intercepts Model (Also Including Level-2 Variables) *		Full Random Coefficients Model *	
			Coef.	***p***	**Coef.**	***p***	**Coef.**	***p***	**Coef.**	***p***
Fixed effects										
INTRCPT2 (γ_{00})			3.332439	0.000	3.810316	0.000	3.799161	0.000	3.795070	0.000
Group level (level 2)	Population density	POP2_D (γ_{01}) ‡					−0.000001	0.033	−0.000001	0.024
	Land use balance	ENT (γ_{02}) ‡					−0.091994	0.193	−0.091923	0.191
	Road connectivity	CNN_D (γ_{03}) ‡					−0.000053	0.031	−0.000053	0.034
	Subway availability	AVL_MET_D (γ_{04}) ‡					0.026379	0.036	0.027598	0.029
Individual level (level 1)	Intra-neighborhood trip	TIntMi (γ_{10})			−0.329049	0.000	−0.327185	0.000	−0.321752	0.000
	Intra-district trip	TIntMa (γ_{20})			−0.750560	0.000	−0.747672	0.000	−0.744683	0.000
	Alternative-mode trip (not by automobile as driver + as passenger)	TModA (γ_{30})			0.061358	0.007	0.063422	0.005	0.064001	0.005
	Birth year	MBirth (γ_{40}) †			0.000989	0.241	0.001012	0.229	0.001149	0.172
	Job: homemaker/unemployed/under school age	MJobRD2 (γ_{50})			0.004761	0.896	0.007171	0.842	0.010878	0.764
	Job: professional/engineer	MJobRD3 (γ_{60})			0.135904	0.000	0.136189	0.000	0.135160	0.000
	Job: administrative/office/manager	MJobRD4 (γ_{70})			0.195824	0.000	0.196864	0.000	0.191045	0.000
	Job: sales	MJobRD5 (γ_{80})			0.079907	0.098	0.087049	0.070	0.085388	0.072
	Job: customer service	MJobRD6 (γ_{90})			0.004898	0.921	0.008525	0.863	0.004616	0.927
	Job (two categories were combined): agriculture/fisheries + manufacturing/transportation/general labor	MJobRD7 (γ_{100})			0.157631	0.001	0.160962	0.001	0.149816	0.002
	Job: others	MJobRD9 (γ_{110})			0.065844	0.087	0.067916	0.076	0.073028	0.053
	Household size	HMemb (γ_{120}) †			−0.018707	0.116	−0.018402	0.122	−0.016769	0.163
	Children	HChil (γ_{130}) †			0.004967	0.859	0.004735	0.865	0.002827	0.920
	Automobiles (sedans + vans + trucks + taxis + motorbikes + others)	HAuto (γ_{140}) †			−0.029270	0.310	−0.030334	0.291	−0.022842	0.432
	Sedans/vans	HPriv (γ_{150}) †			0.008107	0.803	0.011434	0.724	0.007560	0.812
	Housing type: row house	HHouTypRD2 (γ_{160})			−0.077421	0.009	−0.067014	0.023	−0.062939	0.031
	Housing type: multi−family house	HHouTypRD3 (γ_{170})			−0.074794	0.013	−0.066457	0.030	−0.070255	0.019
	Housing type: single−family house	HHouTypRD4 (γ_{180})			−0.022230	0.383	−0.014646	0.574	−0.018184	0.480
	Housing type (two categories were combined): officetel + others	HHouTypRD5 (γ_{190})			−0.021687	0.698	−0.007248	0.899	−0.001098	0.985
	Home ownership: *Jeonse* (two-year lease)	HHouOwnD2 (γ_{200})			−0.050395	0.063	−0.050273	0.065	−0.050604	0.062
	Home ownership: tenancy	HHouOwnD3 (γ_{210})			−0.051465	0.367	−0.055372	0.335	−0.061015	0.279
	Home ownership: others	HHouOwnD4 (γ_{220})			−0.057576	0.264	−0.059050	0.249	−0.069941	0.176
	Income: 1–2 million won	HIncomeD2 (γ_{230})			−0.119903	0.004	−0.119815	0.004	−0.117085	0.006
	Income: 2–3 million won	HIncomeD3 (γ_{240})			−0.174290	0.000	−0.177915	0.000	−0.172727	0.000
	Income: 3–5 million won	HIncomeD4 (γ_{250})			−0.175353	0.000	−0.179371	0.000	−0.176584	0.000
	Income: 5–10 million won	HIncomeD5 (γ_{260})			−0.130346	0.017	−0.136805	0.013	−0.125636	0.022
	Income: $\geq$10 million won	HIncomeD6 (γ_{270})			−0.144842	0.100	−0.146652	0.094	−0.180462	0.037

Table 3. *Cont.*

			Null Model		Random Intercepts Model (Including Only Level-1 Variables)		Random Intercepts Model (Also Including Level-2 Variables) *		Full Random Coefficients Model *	
			Coef.	***p***	**Coef.**	***p***	**Coef.**	***p***	**Coef.**	***p***
Random effects										
Level-1 variance (e_{ij})			0.52957		0.34895		0.34888		0.32834	
Level-2 variance (u_{0j})			0.06667	0.000	0.01329	0.000	0.01225	0.000	0.01404	0.000
MBirth variance (u_{4j})									0.00003	0.019
HMemb variance (u_{12j})									0.00921	0.001
HAuto variance (u_{14j})									0.03325	0.000
Deviance (−2LL)			11,776.499745		9361.714076		9405.194477		9359.800033	
Pseudo R_1^2					0.34107		0.34120		0.37999	
Pseudo R_2^2					0.80066		0.81626		0.78941	
Pseudo R^2					0.39246		0.39432		0.42577	

* Deviance test: model improvement $\chi^2(9) = 45.39444$ ($p = 0.000$). † Continuous level-1 variables (a total of five) were centered on their group means. ‡ All level-2 variables were centered around their grand means. Note: For a total of four discrete variables, base categories were "student" (job), "condominium" (housing type), "ownership" (home ownership), and "<1 million won" (income), respectively. Fixed effects were estimated with robust standard errors. R^2 was calculated to show an improvement (variance reduction) from the null model at each level [34,37]—pseudo R_x^2 = [(level-x variance in the null model − the variance in the present model) ÷ the variance in the null model]—and as follows: pseudo R^2 = 1 − (sum of the level-1 and level-2 variance terms in the present model ÷ sum of the terms in the null model) [28,29]. Collinearity was not found to be a critical issue: VIF = 1.036 (HHouOwnD4)–5.361 (HIncomeD4).

Table 4. Multilevel modeling of log trip time (LnTTime) on weekends (n = 7551 trips).

			Null Model		Random Intercepts Model (Including Only Level-1 Variables)		Random Intercepts Model (Also Including Level-2 Variables) *		Full Random Coefficients Model *	
			Coef.	***p***	**Coef.**	***p***	**Coef.**	***p***	**Coef.**	***p***
Fixed effects										
INTRCPT2 (γ_{00})			3.486306	0.000	3.850539	0.000	3.847121	0.000	3.849297	0.000
Group level (level 2)	Population density	POP2_D (γ_{01}) ‡					−0.000001	0.171	−0.000001	0.105
	Land use balance	ENT (γ_{02}) ‡					−0.155377	0.088	−0.172984	0.056
	Road connectivity	CNN_D (γ_{03}) ‡					−0.000036	0.240	−0.000026	0.387
	Subway availability	AVL_MET_D (γ_{04}) ‡					−0.001697	0.909	−0.002298	0.877

Table 4. *Cont.*

			Null Model		Random Intercepts Model (Including Only Level-1 Variables)		Random Intercepts Model (Also Including Level-2 Variables) *		Full Random Coefficients Model *	
			Coef.	***p***	**Coef.**	***p***	**Coef.**	***p***	**Coef.**	***p***
Individual level (level 1)	Intra-neighborhood trip	TIntMi (γ_{10})			−0.134581	0.004	−0.134039	0.004	−0.121428	0.008
	Intra-district trip	TIntMa (γ_{20})			−0.790325	0.000	−0.791172	0.000	−0.793413	0.000
	Alternative-mode trip (not by automobile as driver + as passenger)	TModA (γ_{30})			−0.003038	0.908	0.000020	0.999	0.001625	0.949
	Birth year	MBirth (γ_{40}) †			−0.000191	0.839	−0.000209	0.824	0.000035	0.971
	Job: homemaker/unemployed/under school age	MJobRD2 (γ_{50})			0.054128	0.155	0.052674	0.166	0.051406	0.171
	Job: professional/engineer	MJobRD3 (γ_{60})			0.039638	0.247	0.038902	0.256	0.035802	0.292
	Job: administrative/office/manager	MJobRD4 (γ_{70})			0.069268	0.037	0.069645	0.036	0.069300	0.032
	Job: sales	MJobRD5 (γ_{80})			0.047839	0.359	0.045265	0.384	0.046589	0.362
	Job: customer service	MJobRD6 (γ_{90})			−0.001374	0.976	0.000152	0.997	0.003069	0.945
	Job (two categories were combined): agriculture/fisheries + manufacturing/transportation/general labor	MJobRD7 (γ_{100})			0.110787	0.023	0.110859	0.023	0.108292	0.022
	Job: others	MJobRD9 (γ_{110})			0.075592	0.061	0.075510	0.061	0.072786	0.061
	Household size	HMemb (γ_{120}) †			−0.003569	0.752	−0.003543	0.753	−0.001596	0.892
	Children	HChil (γ_{130}) †			0.030203	0.437	0.030858	0.426	0.037577	0.339
	Automobiles (sedans + vans + trucks + taxis + motorbikes + others)	HAuto (γ_{140}) †			−0.038681	0.132	−0.038988	0.129	−0.046038	0.113
	Sedans/vans	HPriv (γ_{150}) †			0.015202	0.664	0.017027	0.628	0.013277	0.722
	Housing type: row house	HHouTypRD2 (γ_{160})			0.033147	0.369	0.037794	0.311	0.043425	0.249
	Housing type: multi-family house	HHouTypRD3 (γ_{170})			−0.004025	0.903	0.001160	0.972	−0.004632	0.889
	Housing type: single-family house	HHouTypRD4 (γ_{180})			0.005029	0.865	0.009188	0.759	0.006970	0.820
	Housing type (two categories were combined): officetel + others	HHouTypRD5 (γ_{190})			0.083100	0.245	0.088474	0.219	0.092240	0.198
	Home ownership: *Jeonse* (two-year lease)	HHouOwnD2 (γ_{200})			0.068442	0.056	0.069910	0.051	0.066958	0.054
	Home ownership: tenancy	HHouOwnD3 (γ_{210})			−0.044102	0.481	−0.050841	0.424	−0.052840	0.384
	Home ownership: others	HHouOwnD4 (γ_{220})			0.141862	0.030	0.139677	0.031	0.112346	0.108
	Income: 1–2 million won	HIncomeD2 (γ_{230})			−0.064683	0.174	−0.064966	0.173	−0.062922	0.189
	Income: 2–3 million won	HIncomeD3 (γ_{240})			−0.073149	0.137	−0.075770	0.123	−0.071268	0.151
	Income: 3–5 million won	HIncomeD4 (γ_{250})			−0.123373	0.015	−0.125815	0.013	−0.133888	0.009
	Income: 5–10 million won	HIncomeD5 (γ_{260})			−0.132253	0.028	−0.134832	0.026	−0.133813	0.030
	Income: ≥10 million won	HIncomeD6 (γ_{270})			0.043801	0.654	0.043647	0.657	0.033884	0.734
Random effects										
Level-1 variance (e_{ij})			0.59537		0.44601		0.44581		0.41696	
Level-2 variance (u_{0j})			0.06495	0.000	0.03823	0.000	0.03788	0.000	0.04059	0.000

Table 4. *Cont.*

	Null Model		Random Intercepts Model (Including Only Level-1 Variables)		Random Intercepts Model (Also Including Level-2 Variables) *		Full Random Coefficients Model *	
	Coef.	***p***	**Coef.**	***p***	**Coef.**	***p***	**Coef.**	***p***
MBirth variance (u_{4j})							0.00004	0.001
HMemb variance (u_{12j})							0.00957	0.001
HAuto variance (u_{14j})							0.05299	0.000
Deviance (−2LL)	17,869.808912		15,532.279516		15,579.442605		15,490.205456	
Pseudo R_1^2			0.25087		0.25121		0.29966	
Pseudo R_2^2			0.41139		0.41678		0.37506	
Pseudo R^2			0.26666		0.26749		0.30708	

* Deviance test: model improvement $\chi^2(9) = 89.23715$ ($p = 0.000$). † Continuous level-1 variables (a total of five) were centered on their group means. ‡ All level-2 variables were centered around their grand means. Note: For a total of four discrete variables, base categories were "student" (job), "condominium" (housing type), "ownership" (home ownership), and "<1 million won" (income), respectively. Fixed effects were estimated with robust standard errors. R^2 was calculated to show an improvement (variance reduction) from the null model at each level [34,37]—pseudo R_x^2 = [(level-x variance in the null model − the variance in the present model) ÷ the variance in the null model]—and as follows: pseudo R^2 = 1 − (sum of the level-1 and level-2 variance terms in the present model ÷ sum of the terms in the null model) [28,29]. Collinearity was not found to be a critical issue: VIF = 1.035 (HHouOwnD4)–5.354 (HIncomeD4).

5. Results

5.1. Null Model

At the stage of the null model, the ICCs in the weekday and weekend models were 11.182% [=0.06667/(0.06667 + 0.52957)] and 9.836% [=0.06495/(0.06495 + 0.59537)], respectively, both of which are at the acceptable level. They are particularly so if compared with those reported in previous studies. For example, in Mercado and Páez's study [10] conducted in the Hamilton Census Metropolitan Area, Canada, the ICC was reported as low as 1.25–4.50%. Similarly, Schwanen et al. [28] used the Dutch DUS (daily urban system) as the spatial unit in which only 1.6% was explained at the local/city level. (In addition, in the preceding study [30], the ratio of variance accounted for by the upper spatial level was just 2.2%.) This may indicate that as acknowledged by the authors—"[i]t could be argued that the relevance in the model of the level of the municipality is not very great" (p. 421)—the spatial grouping was not defined at the level at which trips are affected by land use variables. The spatial unit of this study is the finest scale on which spatial data are aggregated: the neighborhood. Indeed, Greenwald and Boarnet [39] argued that land use exerts an influence at the neighborhood level, not at the regional level, and land use should be measured at this level.

5.2. Random Intercepts Model: Inserting Level-One Variables

Inasmuch as the null model secured the legitimacy of multilevel modeling, this study developed a random intercepts model by firstly inserting level-one variables. Notably, it used group mean centering of the variables if they are continuous. (For discrete variables, this study used grand mean centering and in this case, the intercept means log trip time when the very variables have the means of the *total* sample.) As such, the level-one model is dedicated to the estimation of the within-group effect, that is, how an individual-level variable within the group affects the dependent variable while the level-two model is used to estimate the between-group effect, which indicates the effect that a variable has not directly on the individual, but on the mean value of the group.

As presented in the second column of Tables 3 and 4, the random intercepts models with only level-one variables substantially increased the proportions of explained variance. On weekdays, the level-one variance was reduced from the null model by 34.107% [=(0.52957 − 0.34895)/0.52957], indicating that individual characteristics explained 34.107% of the between-individual difference (variance) in log trip time. The weekend random intercepts model also reduced the level-one variance from the null model by 25.087%.

5.3. Random Intercepts Model: Inserting Level-Two Variables

When the random intercepts models additionally included level-two variables, the level-two variance was consistently lower both on weekdays and weekends compared to the models with only level-one variables (see the third column of Tables 3 and 4). Based on the total variance, pseudo R^2 increased from 0.39246 to 0.39432 in the weekday model and from 0.26666 to 0.26749 in the weekend model.

However, compared to the random intercepts models with only level-one variables, those with all variables at both levels did not considerably reduce the level-two variance. As such, neither the level-two R^2 ($R_2{}^2$) nor the total R^2 values were substantially improved. This result echoes the finding of previous multilevel modeling studies [28–31].

5.4. (Full) Random Coefficients Model

In random coefficients (RC) models, the dependent variable at level one is affected by a level-one covariate and the slope of this covariate and the intercept are predicted by the random effect of the grouping variable at level two. As such, conducting this form of multilevel modeling is comparable to conducting OLS regression analyses for all neighborhoods by combining the variability of regression lines (due to the multitude of neighborhoods) into one analysis. As employed in this study, full RC models refer to the case when level−two variables are more than one, and the level-one slopes and intercepts are modeled by multiple grouping variables.

To explore level-one variables that have the random effect, this study specified one variable at a time to have a random coefficient. It then conducted the deviance test [deviance = −2LL(log likelihood)]—that is, the χ^2 difference test—and subsequently added random coefficients in descending order of the degree of reduction in the total variance. Until the model is not identified (not converged), this study continued to add significant random coefficients. Ultimately, insofar as the deviance test and the variance of each random coefficient were significant, it allowed for the random variation in birth year (MBirth), household size (HMemb), and number of automobiles (HAuto) both in the weekday and weekend models (the three variables are arranged according to the degree of variance reduction). While the other variables were additionally allowed one by one to have a random coefficient, the variable turned out to be insignificant or no solution was found. Ultimately, for trips on both weekdays and weekends, the full random coefficients model has the following equation. (For symbols, see Tables 3 and 4.)

$$\begin{gathered} \mathrm{LnTTime}_{ij} = \gamma_{00} + \gamma_{01}\,(\mathrm{POP2\_D}_j - \mathrm{POP2\_D\_bar}) + \gamma_{02}\,(\mathrm{ENT}_j - \mathrm{ENT\_bar}) + \gamma_{03} \\ (\mathrm{CNN\_D}_j - \mathrm{CNN\_D\_bar}) + \gamma_{04}\,(\mathrm{AVL\_MET\_D}_j - \mathrm{AVL\_MET\_D\_bar}) + u_{0j} \\ + \gamma_{10}\,(\mathrm{TIntMi}_{ij}) + \gamma_{20}\,(\mathrm{TIntMa}_{ij}) + \gamma_{30}\,(\mathrm{TModA}_{ij}) + (\gamma_{40} + u_{4j})\,(\mathrm{MBirth}_{ij} - \mathrm{MBirth}_j\mathrm{\_bar}) + \\ \gamma_{50}\,(\mathrm{MJobRD2}_{ij}) + \gamma_{60}\,(\mathrm{MJobRD3}_{ij}) + \gamma_{70}\,(\mathrm{MJobRD4}_{ij}) + \gamma_{80}\,(\mathrm{MJobRD5}_{ij}) + \gamma_{90} \\ (\mathrm{MJobRD6}_{ij}) + \gamma_{100}\,(\mathrm{MJobRD7}_{ij}) + \gamma_{110}\,(\mathrm{MJobRD9}_{ij}) + (\gamma_{120} + u_{12j})\,(\mathrm{HMemb}_{ij} - \\ \mathrm{HMemb}_j\mathrm{\_bar}) + \gamma_{130}\,(\mathrm{HChil}_{ij} - \mathrm{HChil}_j\mathrm{\_bar}) + (\gamma_{140} + u_{14j})\,(\mathrm{HAuto}_{ij} - \mathrm{HAuto}_j\mathrm{\_bar}) + \\ \gamma_{150}\,(\mathrm{HPriv}_{ij} - \mathrm{HPriv}_j\mathrm{\_bar}) + \gamma_{160}\,(\mathrm{HHouTypRD2}_{ij}) + \gamma_{170}\,(\mathrm{HHouTypRD3}_{ij}) + \gamma_{180} \\ (\mathrm{HHouTypRD4}_{ij}) + \gamma_{190}\,(\mathrm{HHouTypRD5}_{ij}) + \gamma_{200}\,(\mathrm{HHouOwnD2}_{ij}) + \gamma_{210} \\ (\mathrm{HHouOwnD3}_{ij}) + \gamma_{220}\,(\mathrm{HHouOwnD4}_{ij}) + \gamma_{230}\,(\mathrm{HIncomeD2}_{ij}) + \gamma_{240}\,(\mathrm{HIncomeD3}_{ij}) + \\ \gamma_{250}\,(\mathrm{HIncomeD4}_{ij}) + \gamma_{260}\,(\mathrm{HIncomeD5}_{ij}) + \gamma_{270}\,(\mathrm{HIncomeD6}_{ij}) + e_{ij} \end{gathered} \tag{1}$$

As shown in Tables 3 and 4, the deviances of the full random coefficients models are the smallest among different types of multilevel models. Compared to the random intercepts models, the deviance on weekdays was reduced from 9405.194477 to 9359.800033 and this model improvement was statistically significant: $\chi^2(9) = 45.39444$ ($p = 0.000$). In addition, on weekends, the deviance reduction was significant: $\chi^2(9) = 89.23715$ ($p = 0.000$).

Not only the deviance, but also pseudo R^2 was better in the full RC models. On weekdays, it changed from 0.39432 in the random intercepts model to 0.42577 and on weekends, from 0.26749 to 0.30708. Meanwhile, consistently less variation was explained in the weekend models. It is because weekday trips consist largely of mandatory, structured purposes of travel (e.g., commute and business), but most weekend trips are individualized, and relatively difficult to explain with the same set of variables [6].

5.5. Level-One Variables: Individual Characteristics

Among individual-level variables, firstly, the most notable effect was made by whether the trip itself was internal or not. Regardless of weekdays or weekends, the trip time difference was larger based on the district (i.e., whether it was made within or between districts) than of the neighborhood. Compared to the choice of the neighborhood/district internal trip, which had a consistent negative effect on weekday and weekend trip times, the choice of automobile alternatives such as public transit had a positive effect on weekdays, but no effect on weekends. Among sociodemographic characteristics, while age (birth year), household size (household members and children), and automobile ownership (all automobiles and sedans/vans, only) were found to be insignificant, job types had a significant effect in both models. In the weekday model, compared to the base category of student (in Seoul, students are assigned to the closest school to their home), all jobs made trip time longer, except for the category of customer service (e.g., casher, waiter, janitor, and housekeeper) and that of homemaker/unemployed/under school age. In the weekend model, trip time was longer in the job types of administrators and managers, agriculture/fisheries/manufacturing/transportation/general labor, and others. Lastly, household income worked negatively on trip time. In the weekday model, relative to the base category (less than one million won), all higher-income categories reduced trip time and consistently, the trip time of the highest income range was the shortest. By contrast, the weekend model presented less consistent results. Trip time was shortened only for the household income ranges of 3–5 and 5–10 million won, which represent the middle class in Korea.

Regarding analytical results at level one, firstly, the longer trip time by automobile alternatives on weekdays is arguably attributed to their mechanical characteristics including slower speed [6]; for example, public transit has frequent stops, allowing passengers to board and exit, and runs on a fixed route regardless of the shortest path from the trip origin to the destination. Secondly, the differing result between weekday and weekend trips—the choice of automobile alternatives did not differentiate weekend trip time—may be led by their different levels of flexibility. That is, weekday mandatory/compulsory trips have relatively fixed destinations and departure and arrival times, and the longer time for weekday trips is likely to result not from a longer trip length (i.e., choice of more distant destinations), but from a slower speed of the trip to the same destination (i.e., high traffic volumes) and subsequent congestion, which is particularly severe on weekdays. In contrast, weekend trips have mostly non-mandatory/discretionary purposes, that is, a wide variety of destinations and a low kurtosis of traffic distribution [2].

As have been reported in previous studies as major travel determinants, this study found that the numbers of automobiles and sedans/vans are insignificant. It is possibly because the trip time variation to be explained by them has already been accounted (i.e., controlled) for by a more direct variable, the alternative mode choice. Indeed, trip time is reduced only when it is used for travel, not just because it is owned.

Meanwhile, the insignificance of automobile ownership as well as of age and household size can be somewhat explained by the tendency that by reducing Type I error, multilevel modeling produces more conservative—and more accurate—results in terms of statistical significance. Another possible explanation is that unique urban settings in Seoul caused the insignificance; for example, important lifecycle changes in relation to these variables (e.g., marriage) have been reported to be insignificant in differentiating travel behavior in Seoul [60]. In fact, according to their random effects/slopes, although the *overall* effects across Seoul are insignificant, the variables are suspected to be significant in *some* neighborhoods. In both the weekday and weekend models, all of birth year, household size, and automobiles were significant.

For a closer look, Figure 4 illustrates the random variation in slopes for birth year, household size, and automobiles, respectively; each slope is estimated at the level of aggregation (i.e., neighborhood). The weekday and weekend models consistently show that the birth year variable has a mixed—both positive and negative—relationship with log trip time. Thus, although insignificant as a whole, the age–trip time relationship could be significant in different directions (+/−) in a few neighborhoods.

Unlike the overall insignificance of age, household size, and automobile ownership, job types were significant in both models. In the weekday model, trip time was shorter in the case of a job for which people search usually near their residence or do not have to commute at all. According to their coefficients, the administrative/managerial job increased the time the most and sales or others the least. This result well reflects the spatial distributions and densities of jobs and the tendency that people are willing to travel longer for quality managerial positions) [28]. In the weekend model, trip time was also longer for administrators and managers probably because they have more chances to participate in weekend leisure activities that generate travel [64] or they feel more pressure on the performance of their institutions, which makes them work beyond regularly scheduled hours [65]. Regarding two other significant job types (agriculture/fisheries + manufacturing/transportation/general labor and others) in the weekend model, their commute trips, not leisure trips, seem to have made trip time longer. In most cases in Korea, these jobs have a six- or seven-day working (or shift working) system.

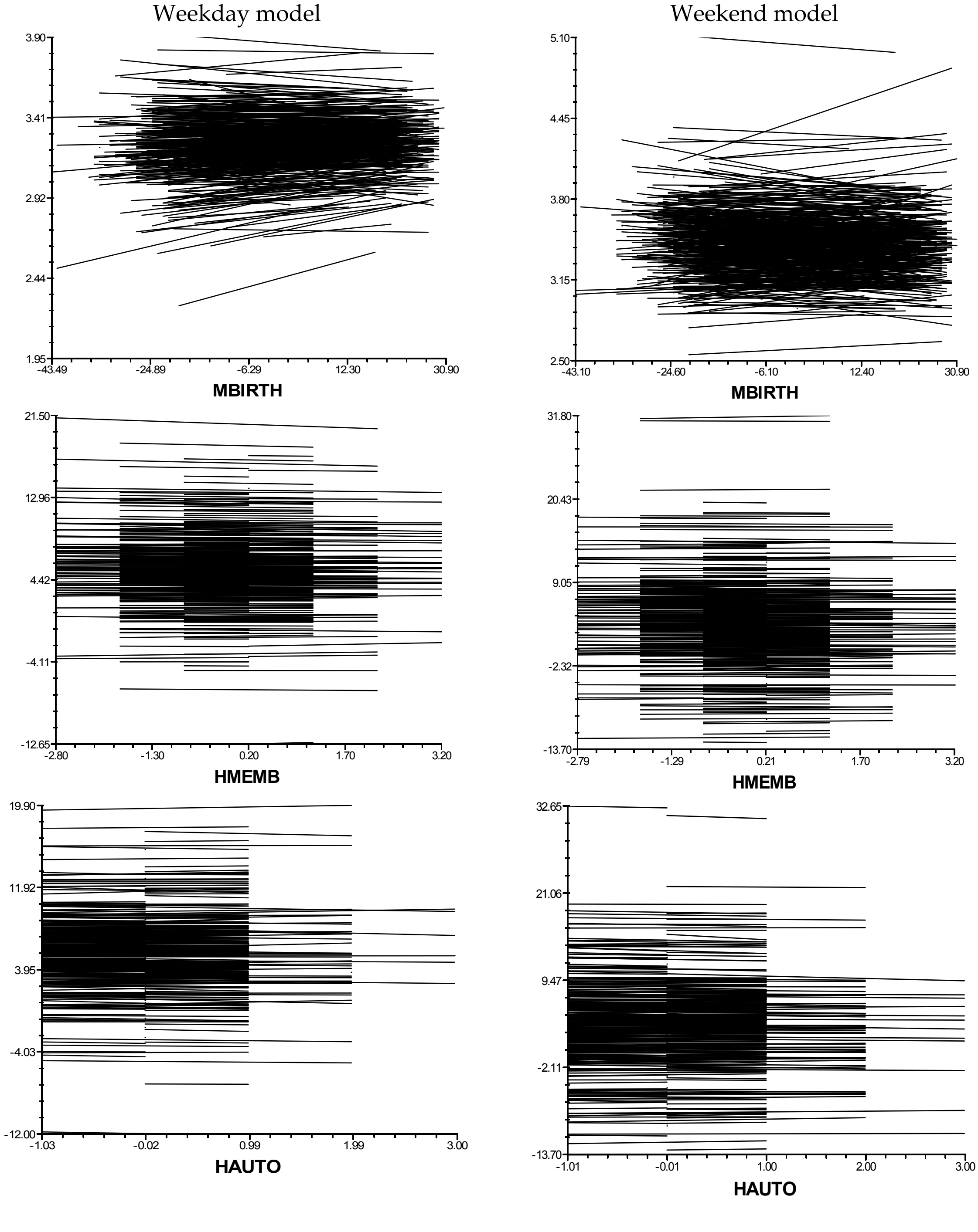

Figure 4. Random slopes of the full random coefficients model: Y-axis = log trip time (LnTTime).

Lastly, the negative relationship between household income and trip time in the weekday model confirms the suspicion that high socioeconomic classes have a high willingness to pay for reducing trip time as travel disutility. On weekends, the middle class spent the shortest trip time: Between the lower class in which a large proportion of people work part-time and the higher class whose wealth is supported by property rental or interest income, the middle class consists mainly of salary workers who often lack free time for leisure.

5.6. Level-Two Variables: Land Use Characteristics

At level two, all of the four variables considered were significant, but they were so in either the weekday or the weekend model, not both: on weekdays, population density (−), road connectivity (−), and subway availability (+) and, on weekends, land use balance (−) only (the signs of the coefficients are in parentheses).

The finding that population density and road connectivity reduce trip time on weekdays is consistent with that of previous studies (e.g., [6,12]). Areas of high density tend to have more population supportive infrastructure and thus, closer destinations. In addition, road connectivity reduces the physical distance to the same destination. In contrast, subway availability was found to have a positive, not negative, effect on trip time, as opposed to our expectation: It was initially expected that closer transit stations would result in shorter access time and accordingly, shorter trip time. Actually, the result can be understood by the function of subway as an automobile alternative. That is, because the automobile is replaced by subway whose mechanical characteristics (e.g., speed) are inferior [6], trip time may be extended. This interpretation is in line with the above finding that among level-one variables, the choice of automobile alternatives has a positive effect on trip time.

The insignificance of land use balance in the weekday trip time model supports and updates the finding of those studies that are based on trip frequency [63,66] and total travel time and mode share [6]: Land use balance is not significant and otherwise significant, the weakest. This study further shows that their finding may also apply to the measure of trip time. Along with studies that analyzed travel measures such as trip frequency, mode share, and travel time and distance, those on the destination choice delivered the same result that the relationship between land use balance and trip internalization is insignificant or virtually zero [67,68].

Meanwhile, Handy and Clifton [13] delivered differing results according to whether they are based on quantitative or qualitative measures. Through quantitative regression of survey data, they found that the addition of local shopping facilities does not reduce automobile travel time. However, according to qualitative focus group interviews, they argued that the addition allows residents to think that automobile travel is not a necessity, but an option or "a matter of choice" (p. 317). In support of this argument, this study empirically found that land use balance mitigates the necessity of automobile travel and ultimately, realizes trip time changes on weekends. In fact, the finding that land use balance affects only weekend trips is in line with the argument of Hong et al. [34] that between business and non-business trips, land use balance facilitates the localization of only non−business trips that are concentrated on weekends.

Overall, high land use balance in a neighborhood may reduce trip time mainly for weekend activities. This suggests that the argument of Giuliano and Small [69] and Gim [6] is persuasive: As a mixed land use policy, a land use balance approach centered on leisure and shopping functions is more desirable than the jobs–housing balance approach, which aims to locate jobs and residences together in a short distance. The land use balance approach will then contribute to the reduction of trip time on weekends (and weekend traffic volume) in particular.

6. Conclusions

There is a growing interest in the characteristics of weekend trips, yet empirical studies—especially those on how they are associated with land use—are few. This study differentiated between weekday and weekend trips in Seoul, Korea to analyze trip time in relationship to land use. A difference from previous studies is that by extracting the same sample of travelers for the two models, this study controlled for the trip time variation due to the sample inconsistency. A second difference is that it used multilevel modeling to correct for Type I estimation error as brought about by specifying an analytical model with variables at different observation levels. (From a different perspective, this study can be differentiated from previous multilevel modeling studies on travel behavior, in the sense that according to a recommendation by Clark et al. [33], it applied multilevel modeling to weekend data as well as to weekday data.) Multilevel modeling is almost always superior to OLS regression, especially in terms of predictive accuracy [70].

For the statistical power of multilevel modeling, this study formatted data to have enough numbers of subjects and groups: The trip was defined as level one (unit of the subject) and the neighborhood as level two (unit of the group). The ICC values presented that the level-two grouping is appropriate to the degree to which trips are affected by grouping land use variables. In general, the trip time variation was found to be better explained by level-one individual variables than by level-two land use variables.

Among level-one individual variables, weekday trip time was found to be reduced not by automobile ownership per se, but by a more direct determinant, the choice of the automobile for travel. In addition, it was longer for jobs that are sparsely distributed—a trip to high-level administrative jobs required the longest time—and for high income travelers.

Among four land use variables at level two, population density, road connectivity, and subway availability were significant only in the weekday model and land use balance only in the weekend model. The significance of population density and road connectivity in the weekday model supports the argument that they reduce the physical distance to destinations. In this sense, policy options that originate from smart growth and compact city concepts can be used to intervene in weekday travel. To increase road connectivity, planners may consider revising subdivision ordinances or street design standards to reduce the number of dead-end streets and their lengths, to create non-motorized travel links to dead-end streets, and to reduce block length and area [71,72]. Regarding density, zoning/building codes may be revised to change minimum and maximum building heights and densities [73,74]; other options for higher density include granting density bonuses as an incentive zoning technique, alleviating requirements on building setback, floor area ratio, and minimum lot size, lowering minimum parking requirements (or establishing maximums), and facilitating approval process for building expansion (e.g., adding rooms or floors), infill development, and redevelopment [75].

Unlike population density and road connectivity, subway availability had a positive, not negative, effect on trip time possibly because of its inferior mechanical characteristics to the automobile. Thus, to be more competitive, subway needs to be improved in terms of its speed and other characteristics such as convenience and timeliness. The finding that land use balance is significant only on weekends supports the argument that this variable is associated particularly with non-business trips. In this sense, the concept of mixed land use would be more effective by considering land uses for leisure, shopping, and other non-mandatory activities, not just for business, namely, jobs–housing balance. From this perspective, local governments may consider revising zoning/building codes and subdivision regulations and granting tax incentives to attract shopping, leisure, and other non-work facilities in residential neighborhoods [75].

A limitation of this study is that it did not consider travelers' attitudes although they are believed to be important travel determinants [6]. This necessitates a primary survey that is equipped with a psychometric technique to test the weekday and weekend models. Secondly, this study attributed the significance of several individual characteristics to the unique settings of Seoul, so a further study is desirable to examine how transferrable the results of the models are to other circumstances. In addition, future studies are recommended to analyze those variables that this study could not consider, such as travel purposes and neighborhood-level traffic volumes and mode shares on weekdays and weekends. Lastly, while studies on the land use–travel relationship are separated according to whether they recruit respondents at trip origins (e.g., residents at the same neighborhoods) or destinations (e.g., employees at the same workplaces) [11], this study falls into the first type of trip origin studies. As such, it measured group-level land use variables at residential neighborhoods, not at trip destinations. However, trip destination characteristics may substantially influence travel decisions. Thus, it is recommended to examine land use characteristics at trip destinations (e.g., spatial distribution of jobs, employment density, and other workplace−related characteristics) as well as at trip origins, considering a wider variety of weekend trip destinations.

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