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Investigating Factors Related to Criminal Trips of Residential Burglars Using Spatial Interaction Modeling

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Abstract: This study used spatial interaction modeling to examine whether origin-specific and destination-specific factors, distance decay effects, and spatial structures explain the criminal trips of residential burglars. In total, 4041 criminal trips committed by 892 individual offenders who lived and committed residential burglary in Tokyo were analyzed. Each criminal trip was allocated to an origin–destination pair created from the combination of potential departure and arrival zones. The following explanatory variables were created from an external dataset and used: residential population, density of residential burglaries, and mobility patterns of the general population. The origin-specific factors served as indices of not only the production of criminal trips, but also the opportunity to commit crimes in the origin zones. Moreover, the criminal trips were related to the mobility patterns of the general population representing daily leisure (noncriminal) trips, and relatively large origin- and destination-based spatial spillover effects were estimated. It was shown that considering not only destination-specific but also origin-specific factors, spatial structures are important for investigating the criminal trips of residential burglars. The current findings could be applicable to future research on geographical profiling by incorporating neighborhood-level factors into existing models.

Keywords: criminal trip; residential burglary; spatial interaction modeling; spatial structure; Tokyo prefecture

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1. Introduction

Investigating how offenders select criminal target areas is one of the main themes in criminology. Many studies have shown that offenders are likely to select areas close to where they live or have lived [1–16] because they are more familiar with such areas and tend to identify suitable targets easily [2,4]. However, the journey-to-crime distances from the offender's residence to the criminal site is related to various factors, including crime scenes [4,14], offender characteristics [6,8–11], and neighborhood-level characteristics such as population density [1,13,16]. Recent studies have shown that the variance of the journey-to-crime distance is explained better by incorporating neighborhood-level variables into the explanatory model [1,16]. On the other hand, in the literature on criminal location choices, it has been noted that the journey-to-crime distances should not be used as the dependent variable: Bernasco and Nieuwbeerta [3] suggested that this distance is just one determinant for the choice of criminal location by an offender and should be regarded as an explanatory variable to explain why offenders prefer certain target areas over others.

1.1. Conditional Logit Model

To overcome the disadvantages of previous studies of criminal location choices, the conditional logit modeling approach has been used. This modeling approach deals with problems of spatial location choices using the utility calculated by spatial alternatives [3] and examines how the choices of criminal locations by offenders are related to neighborhood-level factors as well as the journey-to-crime distances. An advantage of this modeling approach is that it allows the neighborhood-level factors of potential zones that could have been chosen by offenders, but were not, to be incorporated into a model. Bernasco and Nieuwbeerta [3] were the first to use this modeling approach to examine criminal location choices; they found that residential burglars were more likely to choose target zones with many residential units, as well as zones near to where they lived. Likewise, many other studies have indicated that zones that contain many potential targets provide more opportunities for motivated offenders to select a suitable target [7,12,17]. For instance, Hanayama et al. [7] used data on Japanese residential burglaries and found that the number of residential burglaries in the past served as an index of attractiveness for residential burglars. Another advantage of conditional logit modeling is that it allows the differences of spatial choice preferences among offenders to be incorporated into a model [5,12]. For instance, Townsley et al. [12] pointed out that the distances of the criminal trips of residential burglars living in the same origin zone were similar to each other, and Frith et al. [5] found that the street segment that tended to be selected for offending varied across offenders.

These findings indicate that considering neighborhood-level factors is important for investigating the criminal location choices of offenders. However, there are several limitations to using the conditional logit modeling approach. First, it ignores the spatial spillover effects of criminal trips and the spatial structures of the criminal location choices of offenders [18–20]. Indeed, the spatial patterns of crimes are highly concentrated and are highly stable in specific micro places over time [21]. Furthermore, the occurrence of property crimes including burglary is contagious among neighboring communities [20]. In addition, from the perspective of near-repeat victimization, the occurrence of crimes is highly clustered in space and time [22–27]. Two complementary hypotheses have been suggested to account for near-repeat victimization, namely, the flag account and the boost account, both of which are considered as perspectives for explaining the spatial spillover effect of criminal trips. The flag account supports the view that certain properties victimized in the past effectively advertise their vulnerability and attract many opportunistic offenders. Additionally, the structures of road/rail networks for access from neighboring origin zones to a specific destination zone could be similar. Considering this account, the directions of criminal trips heading for a specific destination could display similar patterns. By contrast, the boost account supports the view that a series of criminal activities is committed by a specific serial offender in a neighborhood in which crimes are concentrated [23]. Considering this account, the directions of criminal trips departing from a specific origin could display similar patterns. Therefore, it is possible to hypothesize that offenders' criminal trips are generated on the basis of specific spatial patterns. That is, if the number of criminal trips on a particular origin–destination (OD) pair is higher, this may directly affect the number of criminal trips on spatially neighboring OD pairs.

Second, the conditional logit modeling approach cannot take origin-specific factors into account, but in fact, offenders are more familiar with the origin zones in which they live [2,4]. Moreover, according to an empirical study by Xiao et al. [15], while the existence of many profitable targets located close to the offenders' origin zones encourages potential offenders to search for suitable targets in or near their own origin zone to minimize travel costs, the absence of suitable targets in their origin zones may encourage offenders to travel further. Considering the results of these studies, origin-specific factors could generate criminal trips departing from origin zones and serve as determinants for whether offenders commit crimes therein.

To deal with these two limitations and understand the criminal trips of offenders more clearly, spatial interaction modeling was used in the present study.

1.2. Spatial Interaction Modeling

Spatial interaction models (SIMs) have been used widely in geographic studies [28–31] and have explained spatial movements such as the migration of people [32,33], commodity flows [34,35], and transit flows [36]. A classical SIM known as the "gravity model" is constructed from three types of components: origin-specific components that characterize the ability of origins to generate flows, destination-specific components that represent the attractiveness of destinations, and travel impedances between origin and destination zones [28]. The gravity model is described as

$$T_{ij} = kO_i^{\beta_o} D_j^{\beta_d} d_{ij}^{\beta_{dist}}, \quad (1)$$

where T_{ij} is the number of trips from origin zone i to destination zone j, O_i represents origin-specific factors related to the number of trips, D_j represents destination-specific factors related to the number of trips, d_{ij} is the distance from origin zone i to destination zone j, and k, β_o, β_d, and β_{dist} are fitting parameters.

Some studies have used a classical SIM to investigate the criminal trips of offenders [37,38]. According to Levine [37], criminal trips from origin zone i to destination zone j can be described using Equation (1). That is, O_i is a function of the predisposition to make a trip, including factors representing lack of opportunities and other disturbances in origin zone i, and D_j is a function of attraction or factors that represent an opportunity to decide whether an offender commits crimes in destination zone j. Although Levine [37] considered only the applicability of the classical SIM for explaining criminal trips, Rengert [38] used it to investigate the criminal location choices of residential burglars in Philadelphia. Rengert [38] found that when the relative accessibility among zones was controlled for, the north and south parts of Philadelphia generated more criminal trips than did the central part. However, a limitation of the classical SIM is that it ignores the spatial spillover effect, that is, the spatial structure of OD pairs [28]. To deal with this problem, an expanded SIM that accounts for the influence of the spatial spillover effect and spatial structures has been applied [28,35,36]. In the present study, the expanded SIM was used to explain the criminal trips of offenders because it could properly explain the spatial spillover effect of the crimes discussed above.

1.3. Daily Trips

Referred to as "distance decay", the reduction of movement with increasing distance is commonly observed in the spatial behavior of criminal activity, as well as noncriminal spatial activity such as shopping, traveling, migration, and commuting [4]. According to crime pattern theory, offenders have noncriminal daily spatiotemporal movement patterns: they spend most of their time in noncriminal activities, and crimes occur when the potential offenders locate a suitable target or a victim that fits within their opportunity to commit crimes [39]. Boivin and D'Elia [40] found that the number of noncriminal interzonal trips was a significant positive predictor of the number of criminal interzonal trips in a large city in Canada. This finding supports crime pattern theory, but it is unclear what types of noncriminal trips or daily mobility of the general population can explain criminal trips more clearly. Komaki [41] analyzed data on Japanese noncriminal trips (i.e., daily trips) and found that the patterns of daily spatial movements differed between daily commuting trips and daily consuming (leisure) trips. Using data from a person trip (PT) survey, Komaki [41] investigated the functional structure of the Tokyo metropolitan area and showed that consuming (leisure) trips tended to be dispersed in the study area because the suburbs contained several small-scale consumer areas. By contrast, commuting trips tended to be concentrated in the central business district. Therefore, considering the location choices of residential burglars, the patterns of their criminal trips could be more similar to those of daily consuming (leisure) trips than those of daily commuting trips because the distribution of potential targets (i.e., residences) would be dispersed in the study area like several small-scale consumer areas.

1.4. Hypotheses of Present Study

The aim of the present study was to examine the factors related to the criminal trips of residential burglars using expanded SIMs. To accomplish this purpose, the following three hypotheses were formulated.

Hypothesis 1 (H1). *As noted in previous studies, destination-specific factors can help to explain the criminal trips of residential burglars. In particular, residential burglars tend to select zones in which many residential burglaries have occurred. Namely, zones with a high density of residential burglaries tend to be selected by residential burglars coming from other origin zones.*

Hypothesis 2 (H2). *The criminal trips of residential burglars are associated with origin-specific factors. In particular, this study formulated following two sub-hypotheses.*

Hypothesis 2a (H2a). *Zones with a large residential population tend to generate many criminal trips of residential burglars because many motivated offenders might be included in such zones.*

Hypothesis 2b (H2b). *Zones with a high density of residential burglaries tend to be chosen by residential burglars living in such zones because offenders may first search for suitable targets in or near their own residential zones to minimize travel costs [15].*

Hypothesis 3 (H3). *Spatial structures can help to explain the criminal trips of residential burglars more clearly. In particular, this study formulated following three sub-hypotheses.*

Hypothesis 3a (H3a). *As mentioned above, daily leisure trips constitute a positive predictor of the number of criminal trips compared to daily commuting trips.*

Hypothesis 3b (H3b). *Considering the spatial spillover effect of criminal trips described above, residential burglars who select the same destination zone come from neighboring origin zones. This tendency is referred to as the origin-based spatial spillover effect [28] and is shown in the left-hand side of Figure 1. The solid arrow from origin i to destination j represents the observed criminal trip on a particular OD pair, and the dashed arrows represent criminal trips on OD pairs that are spatial neighbors of the solid arrow. This spillover effect may relate to the flag account because travelers living in the neighboring origin i are assumed to be different offenders, and this diagram indicates that a specific destination (i.e., destination j) is chosen repeatedly by different offenders.*

Hypothesis 3c (H3c). *Residential burglars who come from the same origin zone select neighboring destinations. This tendency is referred to as the destination-based spatial spillover effect [28] and is shown in the right-hand side of Figure 1. This spillover effect may relate to the boost account because travelers living in the same origin zone i could be considered as being the same offender. In the present study, these two spatial spillover effects were incorporated in the model.*

To test these hypotheses, the four models described in Section 2 were constructed.

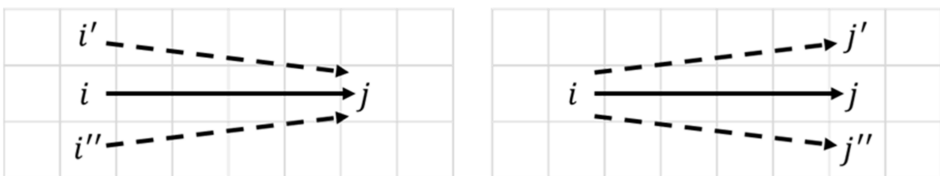

Figure 1. Spatial spillover effects. **Left**: origin-based; **Right**: destination-based.

2. Methods

2.1. Study Area

The prefecture of Tokyo, which is the capital of Japan, was selected as the study area. The estimated residential population of Tokyo is more than 13 million people, and its area is about 2194 km^2. Tokyo is commonly divided into three regions: 23 special wards in its eastern part, the Tama region comprising 26 cities, three towns, and one village in its western part, and two island chains—the Izu Islands and the Ogasawara Islands—in the Pacific Ocean. However, these two island chains were omitted from the study area because they are more than a hundred kilometers from the mainland.

The study area was divided into 53 administrative districts (municipalities), namely, 23 special wards, 26 cities, three towns, and one village. Each of these 53 municipalities was regarded as an analytical unit and is referred to hereinafter as a "zone". Figure 2 shows the location of the study area, and Figure 3 shows choropleth maps of the study area colored by the size of the residential population and population density of each zone. These choropleth maps were created from the census of Japan in 2010. The small circles within each zone displayed in the choropleth maps indicate the locations of public offices. Chiyoda-ku ("ku" means "ward") is a ward that contains many central political institutions. Although many people commute to Chiyoda-ku, its residential population and population density are the smallest of the special wards. Chuo-ku and Minato-ku located adjacent to Chiyoda-ku are also political and economic centers of Japan, and these three wards are commonly referred to collectively as the "center of Tokyo". Meanwhile, Shinjuku-ku, Shibuya-ku, and Toshima-ku are commonly referred to collectively as the "subcenter of Tokyo", which is the commercial center. Setagaya-ku located in the southwestern part of the special wards has the largest residential population in Tokyo. In contrast to the special wards, the Tama region is commonly regarded as the suburb area. The zone with the largest residential population in the Tama region is Hachioji-shi ("shi" means "city"), which is located in its southwestern part. Hachioji-shi has the third-largest residential population in Tokyo. The zone with the second-largest residential population in the Tama region is Machida-shi, which is located adjacent to Hachioji-shi. While Hachioji-shi and Machida-shi have larger residential population in the Tama region, the population density of these cities is relatively small. The zone with the smallest residential population in Tokyo is Hinohara-mura ("mura" means "village"), and the zone with the second-smallest residential population in Tokyo is Okutama-machi ("machi" means "town"). These are located in the western part of the Tama region.

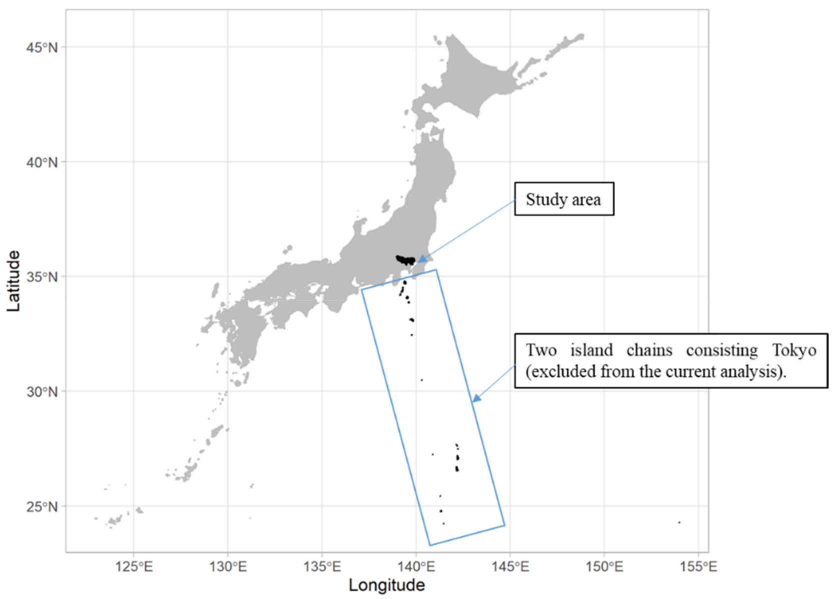

Figure 2. Location of study area.

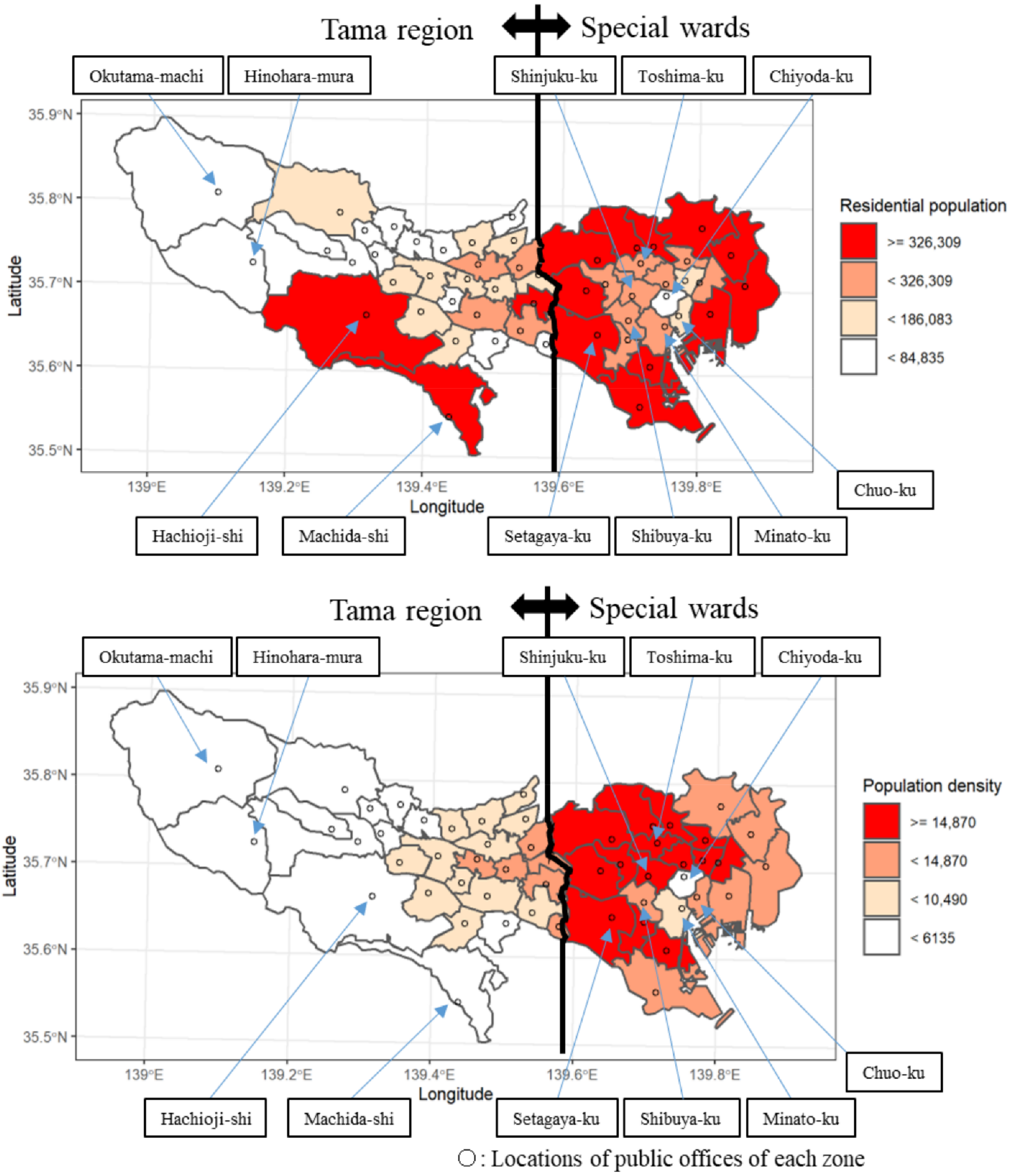

Figure 3. Residential population and population density of each zone.

2.2. Data on Criminal Trips

Data on the criminal trips of residential burglars were obtained from the National Police Agency, from which were extracted individual offenders who lived and committed residential burglaries in Tokyo and were arrested between 2009 and 2017. The following cases were excluded from the analyses because it was difficult to define the departure and/or arrival zones of criminal trips: cases committed by multiple offenders; cases committed by offenders who had no fixed home address at the time of offending; cases in which the block numbers of offenders' home addresses and/or addresses of crime scenes were not identified. The final sample consisted of 4041 criminal trips conducted by 892 residential burglars. The total number of arrested single perpetrators who lived and committed residential burglaries in Tokyo between 2009 and 2017 reported to the

National Police Agency was 1632, indicating that the current sample accounted for 54.7% of all arrested offenders. The reason for the relatively small remaining sample was that only those cases in which the block numbers of offenders' home addresses and addresses of crime scenes were completely identified were included in the subsequent analyses. Offenders committed 4.5 residential burglaries on average (min =1.0, 1st quantile = 1.0, Mdn = 1.0, 3rd quantile = 3.0, max = 151.0), and 324 offenders committed two or more residential burglaries. The average journey-to-crime distance in the current sample was 5.1 km (min = 0.01 km, 1st quantile = 0.94 km, Mdn = 2.81 km, 3rd quantile = 6.61 km, max = 46.05 km).

However, because SIMs require individual criminal trips to be aggregated into OD flow data connecting origin and destination zones, the journey-to-crime distances were transformed into the distances from the central point of the origin zone in which the offender lived to the central point of the destination zone containing the criminal site; the transformation method is described later. The average transformed distance in the current sample was 5.3 km (min = 0.22 km, 1st quantile = 1.11 km, Mdn = 2.62 km, 3rd quantile = 6.58 km, max = 46.33 km). Figure 4 shows the relationship between the journey-to-crime distances and the distances connecting the central points between OD pairs, and a high correlation ($\rho = 0.753$, $p < 0.001$) is observed between them.

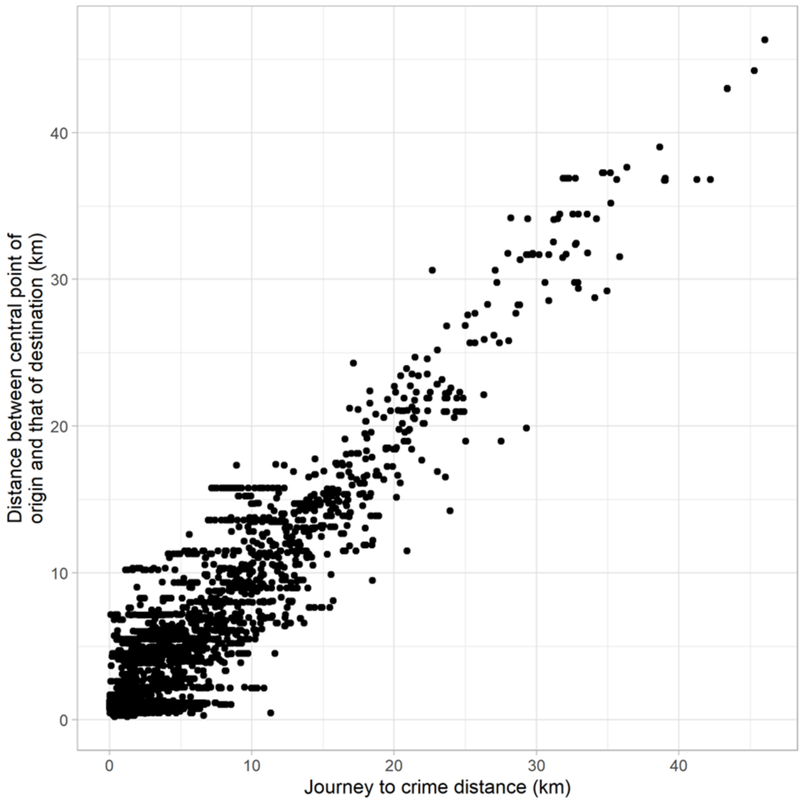

Figure 4. Relationship between journey-to-crime distances and distances connecting central points between origin and destination zones.

Next, potential OD pairs were created from the combination of potential departure and arrival zones in the study area. In the present study, 2809 potential OD pairs (53 zones $\times$ 53 zones) were created, among which 53 OD pairs represented intrazonal trips for which the departure and arrival zones were the same, while the remaining 2756 OD pairs represented interzonal trips for which the departure and arrival zones were different. A criminal trip of a residential burglar was allocated to one of the OD pairs based on the information about the associated departure and arrival zones. The average number of criminal trips on OD pairs was 1.4 (min = 0, 1st quantile = 0, Mdn = 0, 3rd quantile = 0, max = 202). Of all of the potential OD pairs, 17.9% had at least one criminal trip, indicating that the criminal trips generated by the current sample were concentrated in specific OD pairs.

2.3. Variables

To create variables, three external datasets were used in this study. First, sociodemographic data for Tokyo were extracted from the results of the Japanese census. In Japan, a census is conducted every five years, with the most recent surveys dating from 2020, 2015, and 2010. To match the census period with that of other data, the 2010 census was used, and its data were extracted from the "e-stat" portal for official statistics in Japan [42]. Information about the residential population was obtained from the census. As mentioned above and shown in Figure 3, Setagaya-ku had the largest residential population in Tokyo. Descriptive statistics of this variable are presented in Table 1. The distribution of this variable was log-transformed because it was highly skewed.

Table 1. Descriptive statistics of variables.

Variables	Min	1st Qu.	Median	3rd Qu.	Max	Mean	SD
Residential population	2558	84,835	186,083	326,309	877,138	247,766	210,953
Density of residential burglaries	0.01	1.85	3.43	5.43	15.68	4.27	3.42
Daily commuting trips	0	40	207	984	109,434	1795	6227
Daily leisure trips	0	0	44	219	199,115	1491	10,585

Second, the data on the number of residential burglaries reported to the police were used, which were extracted from the portal of the Tokyo Metropolitan Police Department [43]. Although the number of residential burglaries reported to the police is recorded every year, the record in 2010 was used to match the census period. In addition, because the numbers of residential burglaries reported to the police are recorded per district units, which are smaller than municipality units, they were integrated into municipality units. To calculate the density of residential burglaries per zone, the number of residential burglaries was divided by the area. The descriptive statistics are presented in Table 1.

Third, data on daily trips were used, which were created from a PT survey in the Tokyo metropolitan area conducted by the local government [44]. A PT survey is a fundamental survey designed to capture the movements of people on a weekday and clarify their travel attributes, origin and destination points, purpose of trip, and means of transportation for use in urban planning and disaster prevention planning [45,46]. Unlike the census, a PT survey in the Tokyo metropolitan area is only conducted every ten years, with the most recent surveys dating from 2018 and 2008. To match the period of the PT survey with that of the other datasets as much as possible, the data of the 2008 PT survey were used.

The procedure for the 2008 PT survey was as follows. People older than four years of age living in the Tokyo metropolitan area were selected randomly from the basic resident registration data. Respondents received the questionnaire by mail and were required to answer it and then return it by either email or post. The questionnaire had two sections: first, the respondents had to give their demographic attributes (e.g., sex, age, occupation, annual household income), and then they had to describe their daily trips on a weekday (e.g., purpose, origin and destination, means of transportation).

In the present study, a daily trip was defined as movement from the origin zone (municipality) containing the traveler's residence to the destination zone (municipality). The following types of daily trip were excluded from the analyses: trips that started or arrived outside Tokyo, trips that started from the office where the traveler worked, trips from a destination to the traveler's residence, and trips for which either the departure or arrival zone (municipality) was unidentified. After that, the remaining daily trips were classified into two types based on purpose of trip as given by respondents: commuting trips (i.e., movements from travelers' residences to offices) and leisure trips (e.g., for shopping, visiting public facilities, and other trips for private activities). Finally, 5,043,175 daily commuting trips and 4,160,553 daily leisure trips were used in the following analyses, and these trips were allocated to the OD pairs based on the information about departure and arrival zones. The descriptive statistics of these two types of daily trips are presented in Table 1.

2.4. Specification of SIMs

In the present study, the following SIMs were constructed. The objective variable y is an $n^2 \times 1$ vector with elements $\boldsymbol{y}_{ij}$, which is the number of criminal trips from the origin zone i $(i = 1, 2, \ldots, n)$ to the destination zone j $(j = 1, 2, \ldots, n)$ in an OD pair. The base model (Model 0) described by a Poisson regression model is formulated as

$$\boldsymbol{y} \sim \boldsymbol{\mathcal{P}}(\boldsymbol{\lambda}),\ \lambda = \exp\{\alpha \boldsymbol{l}_N + F(\boldsymbol{D})\}, \tag{2}$$

where $\boldsymbol{\mathcal{P}}(\cdot)$ denotes the Poisson distribution, $\boldsymbol{l_N}$ denotes an $n^2 \times 1$ vector (intercept), and α is a scalar parameter to be estimated. The function $F(\boldsymbol{D})$ indicates the impedance between origin i and destination j and is expressed as

$$F(\boldsymbol{D}) = \beta_{dist}\boldsymbol{d}, \tag{3}$$

where $\boldsymbol{d}$ is an $n^2 \times 1$ vector with elements d_{ij}, which is the Euclidean distance between the central point of origin zone i and that of destination zone j, and β_{dist} is a scalar parameter to be estimated. In the present study, the locations of public offices in Figure 3 were regarded as the central points of the zones because public offices are commonly located at the centers of municipalities. In addition, when constructing a SIM, it is necessary to consider the intrazonal distance problem [47]. Several previous studies have examined methods for preventing the distances of intrazonal trips (i.e., $i = j$) from being zero [47,48]. A classical method for dealing with this problem is to assume that the zone is roughly circular and the population is spread evenly with constant density [47]; with this assumption, d_{ii} is calculated as

$$d_{ii} = \frac{r_i}{\sqrt{2}}, \tag{4}$$

where r_i is the radius of zone i. Another method is to consider a mean density of targets in zone i [48]; this is the method used in the present study, and it is calculated as

$$s_i = \frac{A_i}{m_i} \tag{5}$$

and

$$d_{ii} \approx 0.427{s_i}^{-0.5}, \tag{6}$$

where A_i is the area and m_i is the number of residential burglaries reported to the police in 2010.

To test Hypothesis 1 and Hypothesis 2, Model 1, incorporating origin- and destination-specific variables into Equation (2), is constructed as

$$\boldsymbol{\lambda} = \exp\Big\{\alpha \boldsymbol{l}_N + \beta_{o_{pop}}\boldsymbol{x}_{o_{pop}} + \beta_{o_{crim_{intra}}}\boldsymbol{x}_{o_{crim_{intra}}} + \beta_{d_{crim_{inter}}}\boldsymbol{x}_{d_{crim_{inter}}} + F(\boldsymbol{D})\Big\}. \tag{7}$$

Variable $\boldsymbol{x}_{o\_pop}$ is an $n^2 \times 1$ vector indicating the size of residential population in the origin zones. Variables $\boldsymbol{x}_{o_{crim_{intra}}}$ and $\boldsymbol{x}_{d_{crim_{inter}}}$ are $n^2 \times 1$ vectors indicating the density of residential burglaries in the origin or destination zones. To distinguish factors related to interzonal trips from those related to intrazonal trips, they are expanded as follows [28]:

$$\boldsymbol{x}_{o_{crim_{intra}}} = \boldsymbol{x}_{o\_crim} - \boldsymbol{x}_{o_{crim_{inter}}} \tag{8}$$

and

$$\boldsymbol{x}_{d_{crim_{inter}}} = \boldsymbol{x}_{d\_crim} - \boldsymbol{x}_{d_{crim_{intra}}}. \tag{9}$$

The $n^2 \times 1$ vector $\boldsymbol{x}_{o_{crim_{inter}}}$ is defined as the n observations associated with intrazonal criminal trips set to zero in the vector $\boldsymbol{x}_{o\_crim}$. That is, $\boldsymbol{x}_{o_{crim_{intra}}}$ can capture the effects of factors related to intrazonal trips. Likewise, the $n^2 \times 1$ vector $\boldsymbol{x}_{d_{crim_{intra}}}$ is defined as the n observations associated with interzonal criminal trips set to zero in the vector $\boldsymbol{x}_{d\_crim}$. That is, $\boldsymbol{x}_{d_{crim_{inter}}}$ can capture the effects of factors related to interzonal trips.

Model 1 includes the following factors. As an origin-specific factor ($\boldsymbol{x}_{o\_pop}$), the size of the residential population in the origin zones was incorporated. As another origin-specific factor related to intrazonal trips ($\boldsymbol{x}_{o_{crim_{intra}}}$), the density of residential burglaries in origin zones was incorporated. As a destination-specific factor related to interzonal trips ($\boldsymbol{x}_{d_{crim_{inter}}}$), the density of residential burglaries in destination zones was incorporated. The impedance function $F(\boldsymbol{D})$ in Equation (7) was equal to that of Equation (3).

Finally, to test Hypothesis 3, Model 2, incorporating three types of spatial structures, is formulated. First, to incorporate the daily commuting and leisure trips from origin i to destination j representing the movements of the general population on a weekday into the impedance function $F(\boldsymbol{D})$, Equation (3) is expanded as

$$F(\boldsymbol{D}) = \beta_{dist}\boldsymbol{d} + \beta_{ct}\boldsymbol{ct} \tag{10}$$

or

$$F(\boldsymbol{D}) = \beta_{dist}\boldsymbol{d} + \beta_{lt}\boldsymbol{lt}. \tag{11}$$

Variable $\boldsymbol{ct}$ is an $n^2 \times 1$ vector with elements ct_{ij}, which indicates the proportion of commuting trips from origin i to destination j in all daily trips defined by adding the number of commuting trips to that of leisure trips. Likewise, variable $\boldsymbol{lt}$ is an $n^2 \times 1$ vector with elements lt_{ij}, which indicates the proportion of leisure trips from origin i to destination j in all daily trips defined by adding the number of commuting trips to that of leisure trips. Regarding d_{ij}, the farther from origin i to destination j, the higher the impedance of movement. Meanwhile, regarding ct_{ij} and lt_{ij}, the larger the proportion of such daily trips from origin i to destination j, the lower the impedances because it is assumed to be easier for offenders to move to a zone in which many daily trips are generated. Because of the high correlation between $\boldsymbol{ct}$ and $\boldsymbol{lt}$ ($\rho = -0.277$, $p < 0.001$), two types of Model 2 were constructed to avoid multicollinearity: Model 2a incorporating Equation (10), and Model 2b incorporating Equation (11).

Second, to capture the origin-based spatial spillover effect, the origin-based spatial lag vector $\rho_o \boldsymbol{W}_o \boldsymbol{y}$ is incorporated into the right-hand side of Model 2. This vector means that the number of observed criminal trips on an OD pair affects that on other OD pairs that have the same destination and neighboring origins with the observed OD pair. Third, to capture the destination-based spatial spillover effect, the destination-based spatial lag vector $\rho_{\boldsymbol{d}} \boldsymbol{W}_d \boldsymbol{y}$ is incorporated into the right-hand side of Model 2. This vector means that the number of observed criminal trips on an OD pair affects that of other OD pairs that have the same origin and neighboring destinations as the observed OD pair. To calculate these spatial spillover effects, flow-based spatial weight matrices are required, which are expressed as follows [28]:

$$\boldsymbol{W}_o = \boldsymbol{W} \otimes \boldsymbol{I}_N \tag{12}$$

and

$$\boldsymbol{W}_d = \boldsymbol{I}_{\boldsymbol{N}} \otimes \boldsymbol{W}. \tag{13}$$

The $n \times n$ spatial weight matrix $\boldsymbol{W}$ in Equations (12) and (13) defines which zones are spatial neighbors, and $\boldsymbol{I}_{\boldsymbol{N}}$ is an $n \times n$ unit matrix. The spatial weight matrix $\boldsymbol{W}$ has the element w_{ij}, which was defined as $-d_{ij}$ in the present study. This means that as the distance between the zones decreases, w_{ij} increases linearly. The Kronecker product ($\otimes$) in Equation (12) multiplies the right-hand argument $\boldsymbol{I}_N$ with each element in the spatial weight matrix $\boldsymbol{W}$. Likewise, the Kronecker product ($\otimes$) in Equation (13) multiplies the right-hand argument $\boldsymbol{W}$ with each element in the unit matrix $\boldsymbol{I}_N$. ρ_o and ρ_d are spatial lag coefficients to be estimated; if these are estimated with relatively large values, then the interpretation is that criminal trips are not generated randomly.

2.5. Indices of Model Fits

To examine which models explained the criminal trips more clearly, the following fitting indices were used. First, the pseudo R-squared measure for Poisson regression was used. In Poisson regression models, an adjusted R-squared measure based on deviances is defined by

$$R_D^2 = 1 - \frac{D(y;\hat{\mu}) + k}{D(y;\overline{y})}, \tag{14}$$

where $D(y;\hat{\mu})$ is the deviance of the model that contains the covariates of interest, $D(y;\overline{y})$ is that of the model with only the intercept included, and k is the number of covariates fitted in the model that contains the covariates of interest. R_D^2 can be interpreted as the relative reduction in deviance due to incorporating covariates into the model [49].

Second, the AIC (Akaike's information criteria) and BIC (Bayesian information criteria) were compared among the models. The model with the smallest AIC and BIC is interpreted as explaining the dependent variable better. Third, Moran's I was calculated for the residuals of each model. For this, the number of incoming trips for each destination j was aggregated. The residual was defined as the difference between the actual and estimated number of incoming trips, divided by the estimated number of incoming trips [36]. If a relatively large Moran's I is observed, then the interpretation is that the model cannot capture the spatial structures of criminal trips properly.

3. Results

3.1. Spatial Patterns of Criminal Trips

The total number of interzonal criminal trips was 2208; that is, 54.6% of residential burglaries were committed by traveling between different zones. The spatial distribution of intrazonal trips is shown in Figure 5. The zones colored bright red are those in which there were many intrazonal trips. The spatial pattern of the intrazonal trips is similar to that of the residential population shown in Figure 3; that is, intrazonal trips were more likely to be observed in the eastern part of the study area comprising the 23 special wards, except for Chiyoda-ku and Chuo-ku. The most intrazonal trips were in Adachi-ku, which is in the northern part of the special wards, whereas few intrazonal trips were in the Tama region, except for Hachioji-shi and Machida-shi.

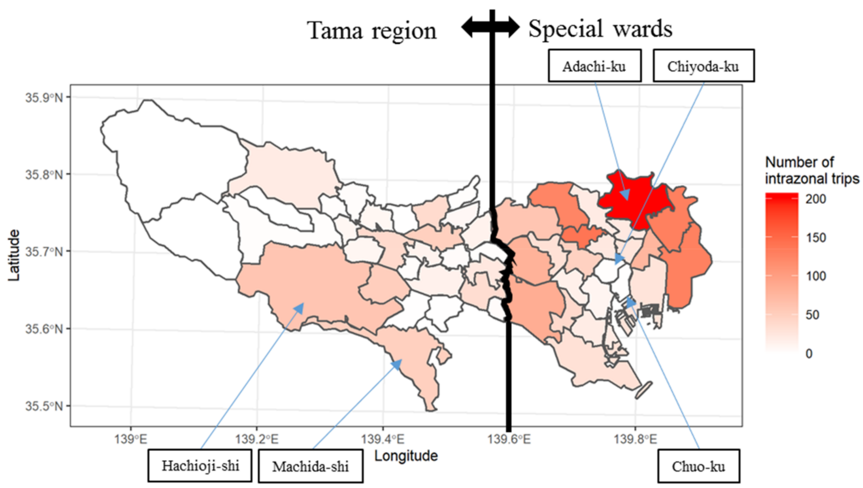

Figure 5. Spatial distribution of intrazonal criminal trips.

The spatial pattern of the interzonal trips is shown in Figure 6, where a straight line connecting zones represents an observed OD pair. Figure 6a comprises only OD pairs with fewer than five interzonal trips, while Figure 6b comprises only OD pairs with five or more interzonal trips. The red straight lines indicate that many criminal trips were observed.

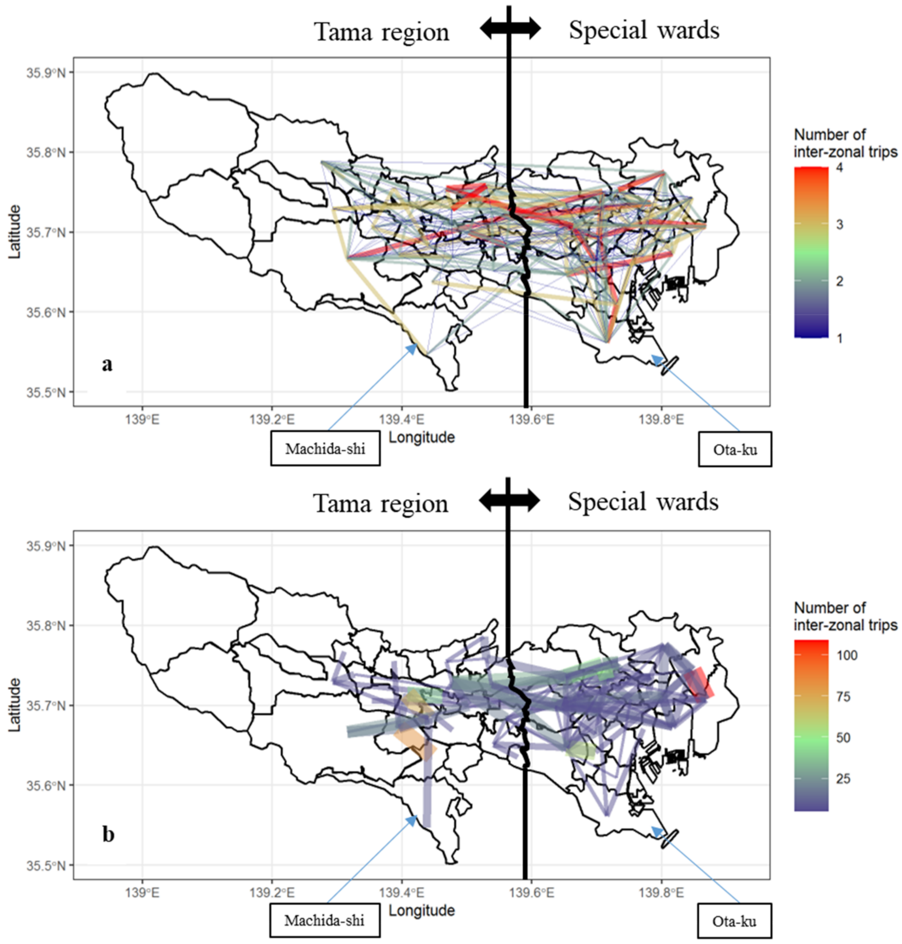

Figure 6. Spatial distribution of interzonal criminal trips: (**a**) OD pairs with fewer than five interzonal trips; (**b**) OD pairs with five or more interzonal trips.

As shown in Figure 6a, for the OD pairs with few interzonal trips, some had longer distances; for example, some OD pairs connected Machida-shi in the southern part of the Tama region with several zones in the special wards, and some connected Ota-ku in the southern part of the special wards with several zones in the Tama region. However, as shown in Figure 6b, for the OD pairs with five or more interzonal trips, almost all had shorter distances; for example, the OD pairs connected with Machida-shi were not connected with the special wards, and the OD pairs connected with Ota-ku were not connected with zones in the Tama region.

3.2. Comparison of Models

First, the base model (Model 0) only incorporating the distance decay effect was constructed (see Table 2). Consequently, a considerable negative distance decay effect was confirmed, indicating that the number of criminal trips decreased with increasing distance between zones. However, Model 0 only explained 38.5% of the deviance, and the Moran's I of the residuals was high (0.244). Therefore, Model 0 was insufficient for explaining the criminal trips of residential burglars and capturing the spatial structures of those trips properly.

Table 2. Results of SIMs.

Factor		Model 0			Model 1			Model 2a			Model 2b		
		Parameter	*SE*	*p*	Parameter	*SE*	*p*	Parameter	*SE*	*p*	Parameter	*SE*	*p*
Distance decay effect (log)		−0.944	0.008	***	−1.267	0.015	***	−1.161	0.020	***	−1.023	0.022	***
Origin-specific factors	Size of residential population (log)				1.052	0.022	***	1.262	0.027	***	1.249	0.027	***
	Density of residential burglaries				0.167	0.005	***	0.137	0.005	***	0.122	0.005	***
Destination-specific factors	Density of residential burglaries				0.081	0.004	***	0.062	0.005	***	0.059	0.005	***
Spatial structures	Proportion of commuting trips							−0.673	0.085				
	Proportion of leisure trips										1.661	0.101	***
	Origin-based spatial lag coefficient							0.221	0.013	***	0.231	0.014	***
	Destination-based spatial lag coefficient							−0.323	0.024	***	−0.324	0.024	***
Model fit	Pseudo R^2	0.385			0.653			0.674			0.681		
	Moran's I (destination based)	0.244			0.147			0.140			0.123		
	AIC	15,692			9539			9061			8884		
	BIC	15,703			9568			9109			8932		

*** $p < 0.001$

To test Hypothesis 1 and Hypothesis 2, Model 1 incorporating origin- and destination-specific factors into Model 0 was constructed. The variance inflation factor (VIF) of Model 1 was under 1.63. While a considerable negative distance decay effect was estimated as with Model 0, considerable relationships were also estimated between the criminal trips and each factor incorporated into the model. Zones with a large residential population were more likely to produce many criminal trips. In addition, zones with a high density of residential burglaries were likely to be selected as the destination zones by residential burglars departing from different zones. Moreover, zones with a high density of residential burglaries were also likely to be selected as the destination zones by residential burglars departing from the same zones. Although Model 1 explained 65.3% of the deviance, the Moran's *I* of the residuals was slightly high (0.147).

Finally, Model 2a and Model 2b, incorporating spatial structures into Model 1, were constructed. The VIFs of Model 2a and Model 2b were under 2.64 and 3.18, respectively. The results of both models showed that the daily trips were a significant predictor of criminal trips. However, the opposite patterns were observed between the commuting trips and the leisure trips. While the proportion of commuting trips included in Model 2a indicated a negative significant predictor of criminal trips, the proportion of leisure trips included in Model 2b indicated a positive significant predictor of criminal trips. In addition, although both types of spatial lag coefficients included in Model 2a and Model 2b were relatively large, the opposite patterns were observed. A relatively large positive origin-based spatial lag coefficient was found, which suggests that more criminal trips on an observed OD pair predicts more criminal trips on OD pairs that have the same destination and neighboring origins as the observed OD pair. On the other hand, a relatively large negative destination-based spatial lag coefficient was found, which suggests that more criminal trips on an observed OD pair predicts fewer criminal trips on OD pairs that have the same origin and neighboring destinations as the observed OD pair. The highest pseudo R^2 and the smallest AIC and BIC were obtained with Model 2b, indicating that criminal trips of residential burglars were explained more clearly when considering not only origin- and destination-specific factors, but also spatial structures, including daily leisure trips. Moreover, the smallest Moran's *I* of the residuals was obtained with Model 2b, indicating that the spatial autocorrelation of residuals was explained by incorporating spatial structures including daily leisure trips into the model.

To visualize the spatial patterns of the estimated total incoming trips, the estimated number of those trips for each zone was calculated. For comparison with these estimated values, the observed number of total incoming trips of each zone was obtained, and the results are shown in Figure 7. The zones colored bright red are those with a high estimated or observed number of total incoming trips. The spatial pattern of the estimated total incoming trips with Model 0 was completely different from that of the observed total incoming trips. However, the spatial patterns of the estimated total incoming trips with Model 1, Model 2a, and Model 2b were similar to those of the observed total incoming trips. In particular, these three models estimated larger numbers of total incoming trips for the special wards, except for Chiyoda-ku and Chuo-ku. In addition, Hachioji-shi and Machida-shi in the southwestern part of the Tama region were estimated as having larger numbers of total incoming trips compared to the other zones in the Tama region. These tendencies were similar to the spatial pattern of the observed total incoming trips.

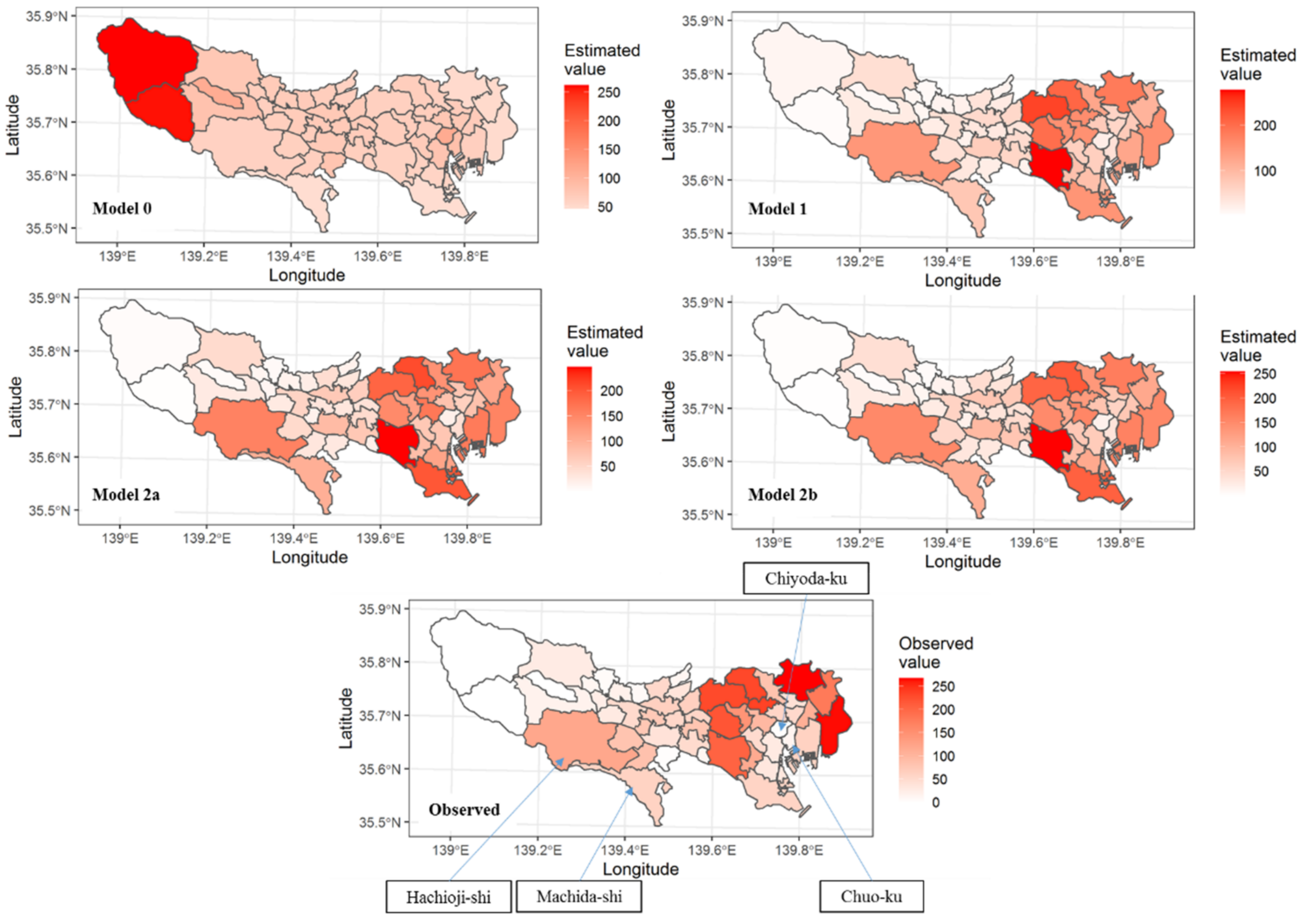

Figure 7. Estimated or observed numbers of total incoming trips.

4. Discussion and Conclusions

The criminal trips of residential burglars were explained more clearly using expanded SIMs. Consistent with previous studies, the destination-specific factors were related to the number of criminal trips of residential burglars. In particular, zones with a high density of residential burglars were more likely to be selected by offenders, which supports Hypothesis 1. This finding is consistent with previous studies of the criminal location choices [3,7,11,17], implying that destination zones with many potential and victimized targets might attract potential offenders.

In addition, the origin-specific factors were associated with the criminal trips of residential burglars. In particular, zones with a large residential population tended to generate more criminal trips, which supports Hypothesis 2a. From the perspective of crime pattern theory [39], this could be interpreted as meaning that a zone with a large residential population might include many motivated potential offenders and generate many criminal trips. In addition, zones with a high density of residential burglaries tended to be chosen by residential burglars living in such zones, which supports Hypothesis 2b. This tendency provides further empirical support for the assertion that offenders might search for suitable targets in their own residential zones before traveling further in order to minimize travel costs [15].

Furthermore, the spatial structures of daily trips and OD pairs explained the criminal trips more clearly. First, the proportion of daily leisure trips helped to explain the criminal trips of residential burglars, implying that the spatial movements of residential burglars are more similar to daily leisure trips than to daily commuting trips, which supports Hypothesis 3a. This tendency might stem from the special nature of the spatial patterns of commuting trips in the Tokyo metropolitan area. Komaki [41] indicated that daily commuting trips in the Tokyo metropolitan area tended to be concentrated in the central business district, whereas, unlike daily commuting trips, the destination zones of daily consuming trips tended to be dispersed because there are several small-scale consumer areas in the suburbs. In light of the results obtained by Komaki [41], it is possible to consider that the distribution of the potential target zones of residential burglaries might be similar to that of daily leisure trips; that is, the potential destination zones of residential burglars might be dispersed in the study area because of the existence of several small-scale target areas.

Moreover, relatively large origin- and destination-based spatial lag coefficients were estimated, implying that an observed OD pair might affect spatially neighboring OD pairs. However, the opposite patterns were estimated between origin-based and destination-based spatial spillover effects. The relatively large positive origin-based spatial lag coefficient indicated that criminal trips arriving at a particular destination zone tended to depart from neighboring origin zones, which supports Hypothesis 3b. This result implies that the criminal trips departing from neighboring origin zones might be concentrated in a particular destination zone. Because the structures of the road/rail network for access from origin to destination might be quite similar among neighboring origin zones, it might be easier for motivated offenders living in neighboring origin zones to access a specific destination zone. In addition, considering the flag account explaining the near-repeat victimization [22,23], this tendency might be interpreted as meaning that destination zones containing many vulnerable properties attract many motivated offenders living in neighboring origin zones and are victimized repeatedly by different offenders. By contrast, the relatively large negative destination-based spatial lag coefficient indicated that criminal trips departing from the same origin zone tended not to arrive at neighboring destination zones. That is, the destination zones of criminal trips tended to disperse in the study area, which does not support Hypothesis 3c. The current study hypothesized a positive destination-based spatial spillover effect because of the boost account that assumes that a series of criminal activities is committed by a specific serial offender in the neighborhood [22–24]. However, because a relatively large analytical unit (i.e., municipality) was used in the current study, many different offenders were included in the same origin zones. As shown by previous studies [5,12], the preferences of spatial criminal location choices vary across offenders. Furthermore, as mentioned above, because the destination zones of residential burglars might be dispersed in the study area because of the existence of several small-scale target areas, different offenders could prefer different target areas. Consequently, negative destination-based spatial spillover effects were observed because of contamination effects at the inter- and intra-offender levels.

The present study produced many findings and suggestions, but it also had several limitations, the first being data availability. The present study used the records of arrested offenders held by the National Police Agency and three external datasets: census data, PT survey data, and statistics for the numbers of residential burglaries reported to the police in Tokyo. Because of the different survey techniques and recording cycles among these external datasets, the present study could not create variables from data recorded in the same year. Moreover, factors in the models such as the size of the residential population, density of residential burglaries, and numbers of daily commuting and leisure trips are not static and can change over time; however, they were regarded as being static, and so their temporal changes could not be captured.

The second limitation concerns the analytical unit. The results of the current study showed that more than half of the criminal trips of the current sample (54.6%) were between municipalities when crime was being committed. Furthermore, a high correlation between the journey-to-crime distances and the transformed distances (i.e., distances from the central point between origin and destination zones) was observed in the current sample (see Figure 4). These results justify defining municipalities as the analytical unit. However, a line of research investigating the relationship between destination-specific factors and location choices of offenders has defined the analytical unit as more detailed zones because the journey-to-crime distances are relatively short [3,7,12,17]. In addition, the spatial patterns of crimes are highly concentrated and are highly stable in specific micro places over time [21–27]. Moreover, Figure 4 shows that larger error distances were observed between the journey-to-crime distances and the transformed distances on a shorter distance scale.

Nevertheless, the analytical unit used in the current study was relatively large in scale and could be insufficient for capturing the crime distribution in the study area. The reason for restricting the analytical unit was that the aggregated unit of the PT survey in the Tokyo metropolitan area is commonly based on the municipality unit. While the current study revealed the relationship between the spatial pattern of criminal trips and that of the general population using the PT survey, further studies are required to investigate the generalizability under different analytical units if more suitable data are available. In addition, it is necessary to examine whether these findings can be applied to other areas, such as nonmetropolitan areas in Japan. Additionally, the estimated spatial spillover effects could be restricted because criminal trips generated from and/or arriving in prefectures neighboring Tokyo were excluded from the present study.

Third, although it has been noted that the journey-to-crime distances differ with offender age, crime scene, and means of transportation [4,6,8–10,14], the current SIMs could not incorporate these factors properly because SIMs require individual criminal trips to be aggregated into the flow data connecting origin and destination zones [3]. Further studies are required to consider the interaction effects between individual and neighborhood levels [17].

Although the present study had several limitations, as discussed above, it formulated three hypotheses and revealed the relationship between the criminal trips of residential burglars and neighborhood-level factors using SIMs. The results showed that the origin-specific factors, including a source of energy-producing criminal trips and the destination-specific factors representing an index of attractiveness for potential offenders, were significant positive predictors of the number of criminal trips. Furthermore, criminal trips were not generated randomly in space and had similar spatial movement patterns to those of daily leisure trips. These results provide several implications for supporting crime pattern theory and accounting for near-repeat victimization. Moreover, these findings could be applied to future research on geographical profiling, incorporating neighborhood-level factors and spatial structures.

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Conflicts of Interest: Although the sixth co-author, Yoshinori Hawai's current affiliation is Insight-Edge, Inc. (Tokyo, Japan), he contributed to our study when he was a member of our research project in National Researh Institute of Police Science. Therefore, the authors declare no conflict of interest.

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