Homeless Networks: Testing Peer and Homed Networks Against Location Choice

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Abstract

This paper examines the location choices of homeless people in Osaka City, and finds them concentrated because of *homeless* networks. The paper also shows that different types of homeless networks operate in two different homeless groups: (1) peer networks that provide a social tie inside homeless communities are observed in groups that had not had work experience in the day labor market; (2) homed networks that provide a social tie outside homeless communities affect location choice in the expected way, although the effect is statistically insignificant in groups that had worked in the day labor market.

Keywords: Homeless networks, homed networks, peer networks, conditional logit model

JEL classification: C25, R23

1 Introduction

The purpose of this paper is to examine the location choice of homeless people in Osaka City by focusing on two components of *homeless* networks: peer networks and homed networks (Rowe and Wolch, 1990; Wolch, Rahimian, and Koegel, 1993).[1]

Peer networks provide an internal link between the homeless individual and members of the homeless community. Homeless friends or members of informal homeless communities share information about work and groceries. (Osaka City University Study Group of Urban Environmental Issues (OCUSG), 2001; Wolch, Rahimian, and Koegel, 1993; Yamakita, 2007). Homeless people also benefit from peers, to protect themselves against harassment from residents (OCUSG, 2001; Okamoto, 2007; Yamakita, 2007). *Homed* networks provide an external link between the homeless individual and members of the homed community. Clustering of homeless people occurs because a network may provide readily available labor for labor recruiters, food services, and flophouse markets for homeless people (Aoki, 2003; Mizuuchi, 2003; Shima, 1999). Furthermore, homeless clustering may establish volunteer groups that support homeless people, e.g., providing a soup run (Mizuuchi, 2003; Okamoto, 2007; Wolch, Rahimian, and Koegel, 1993).

In the economic literature, social networks create geographic agglomeration (Bartel, 1989; Bauer, Epstein, and Gang, 2005; Jaeger 2007). In fact, OCUSG (2001) revealed the distribution of the homeless in Osaka City by census block (the 1998 Homeless Count data), and found them to be geographically concentrated. Therefore, applying homeless networks theory to the location choice of homeless people contributes to an understanding of the geographic concentration of homelessness in Osaka City.[2]

Several empirical studies have examined the spatial distribution of homelessness in metropolitan areas using intercity data (Elliott and Krivo, 1991; Honig and Filer, 1993; Lee, Price-

[1] Homelessness in Japan is defined as people who dwell in a tent or hut in outdoor areas and those who sleep in a cardboard box on a street. Thus in Japan, homeless people are known as *rough sleepers* or *street homeless*. The definition of homelessness in Japan is much narrower than that used in Europe and the US. According to the 2003 Nationwide Survey on the Actual Condition of Homeless People conducted by the Ministry of Health, Labor and Welfare, Osaka City has the largest number of homeless people in Japan.

[2] Wolch, Rahimian, and Koegel (1993) showed that the intraurban mobility pattern of homeless individuals on Skid Row in Los Angeles is linked to homeless networks, especially their homed family and friends. Another line of literature analyzes the relation between homeless networks and economic welfare (Conroy, 2001; Schoeni and Koegel, 1998). Schoeni and Koegel (1998) have shown that homeless people in Los Angeles whose most significant family member also lives in Los Angeles are much more likely to receive assistance.

Spratlen, and Kanan, 2003; Park, 2000; Quigley, Raphael, and Smolensky, 2001). One key determinant of homelessness is the state of the housing market, as suggested by the model of O'Flaherty (1995).

However, less attention has been devoted to the spatial distribution of homelessness within a city. The homeless network may be very localized, consequently intracity-level data are appropriate for estimating the location choice of the homeless.[3] Schor, Artes, and Bomfim (2003) and Suzuki (2007) considered the spatial distribution of homelessness using intracity data. Schor, Artes, and Bomfim (2003) have used a census of homeless people in São Paulo City and applied a regression model to test the spatial distribution of homelessness. They have found that homeless people are concentrated in built-up areas of high-rise buildings for commercial and services usage. Homeless people in São Paulo City prefer these areas, because it provides discarded materials from which to obtain recycling income, and provides leftover food for survival. Using the 1998 Homeless Count data, Suzuki (2007) applied a spatial error model. Suzuki found that homeless people settle near employment agencies and a Kamagasaki *yoseba* to find a new job.[4] A *yoseba* is located in a segregated district where labor recruiters provide jobs to day laborers. The residential area around the *yoseba* consists of inexpensive, single-room-occupancy (SRO) hotels or flophouses. A large number of homeless people in Osaka City come from the Kamagasaki *yoseba*, and search for jobs around Osaka City, especially in the *yoseba*, even after becoming homeless (Aoki, 2003; Mizuuchi, 2003; Shima, 1999). Suzuki (2007) has also shown that the number of public medical care facilities and daily needs food shops within close proximity significantly affect the spatial distribution of homelessness in Osaka City.[5]

The paper does not directly estimate the geography of homeless people. Given the geography of homeless people in the city, we examine the presence of homeless networks on homeless people's location choice within-city. The main data employed in the estimation is the 1999 Interview Survey of Homeless People undertaken by OCUSG (2001). In 1999, OCUSG (2001) collected

[3] To understand the distribution of homeless people within a city is also important to policy makers, because they are concerned with the location of shelters in the city (Lobao and Murray, 2005; Suzuki, 2007).

[4] Marr (1997) and Okamoto (2007) state that the *yoseba* are like American skid rows.

[5] Culhane, Lee, and Wachter (1996) also analyzed the distribution within cities (New York City and Philadelphia). The data are the prior addresses of the shelters used before they became homeless. In this paper, however, we focus on rough sleepers or street homeless, as did Schor, Artes, and Bomfim (2003) and Suzuki (2007).

microlevel data on 672 homeless people who mainly lived in public parks in Osaka City. The survey asked homeless people to report their location. The traditional method of capturing the effect of social ties on location choice has used a preexisting population that belongs to a homogeneous society (Bartel, 1989; Bauer, Epstein and Gang, 2005, Jaeger 2007). People tend to locate around high concentrations of homogeneous people, because they benefit from peers. Fortunately, we could verify the presence of a homeless population from the 1998 Homeless Count data. Combining the two data sets, we can estimate the location choice of homeless people within public parks in Osaka City as the choice set, given the number of preexisting homeless people in the census block where a certain public park is located. Using the conditional logit model, we find that the number of preexisting homeless people is a significant factor in the location decision. This implies that homeless networks do exist in a homeless society.

As mentioned above, the main purpose of the paper is to isolate two components of homeless networks: peer and homed networks. To do this we divide the sample of homeless people into two groups from the viewpoint of a Kamagasaki *yoseba*. The first group of homeless people come from the Kamagasaki *yoseba*, and search for jobs around there even after becoming homeless (Aoki, 2003; OCUSG, 2001; Shima, 1999). The second group had not had work experience in the Kamagasaki *yoseba*. Inexperienced Kamagasaki workers are employed low-skilled workers in the general labor market before they become homelessness (Aoki, 2003). OCUSG (2001) found that the geographic pattern of those groups are different, i.e., the first group settle near the *yoseba*, and the second group settle far from the *yoseba*.[6] Considering this heterogeneity, we again estimate the conditional logit model. The empirical results are consistent with OCUSG (2001): the greater the distance from the *yoseba*, the weaker the link to the *yoseba*. The empirical result also shows that peer networks work in inexperienced Kamagasaki homelessness societies, while homed networks may exist in experienced Kamagasaki homelessness societies. Different kinds of homeless networks will exist between the two groups.

The rest of the paper is organized as follows. Section 2 presents an empirical model of home-

[6] Okamoto (2007) has also shown that two types of homeless person in Nagoya City, based on their geographical location. Those found in the Sasajima *yoseba* and their surroundings were mostly day laborers in construction. Those found elsewhere had held jobs that were not based on the *yoseba* before they became homeless. See also Mizuuchi (2007).

less networks. A conditional logit model is estimated to capture the location choice mechanism of homeless people. Section 3 describes the data used in the empirical models. Section 4 describes the estimated results of homeless networks. Section 5 presents an empirical model of the peer network and the homed network. This section also presents the results of these networks. Section 6 summarizes the main conclusions of the paper.

2 Benchmark Empirical Model

To investigate the determinants of the location choice of homeless people in Osaka City, we estimate a conditional logit model (McFadden, 1974). Each homeless person i faces a choice among J parks in Osaka City. Assume that the utility of choosing park j is given by:

$$u^*_{ij} = \alpha h_{ij} + \boldsymbol{x}'_{ij}\boldsymbol{\beta} + \varepsilon_{ij}$$

where h_{ij} is the number of preexisting homeless people in j that have a coefficient α, $\boldsymbol{x}_{ij}$ is a vector of the spatial-specific attribute in j that has a vector of coefficients $\boldsymbol{\beta}$, and ε_{ij} is an error term.

We observe u_{ij} where:

$$u_{ij} = \begin{cases} 1, & u^*_{ij} = \max\ [u^*_{i1}, u^*_{i2}, \cdots, u^*_{iJ}] \\ 0, & \text{otherwise} \end{cases} .$$

Furthermore, we assume that ε_{ij} is distributed i.i.d. and has an extreme value distribution with a cumulative distribution. According to McFadden (1974), the probability of a homeless person i choosing park j from all candidates for his/her dwelling location is given by the logit expression:

$$\mathrm{Pr}_{ij} = \frac{\exp(\alpha h_{ij} + \boldsymbol{x}'_{ij}\boldsymbol{\beta})}{\sum_{j=1}^{J} \exp(\alpha h_{ij} + \boldsymbol{x}'_{ij}\boldsymbol{\beta})}. \tag{1}$$

The following hypothesis is considered.

Hypothesis 1 *A homeless person i who chooses park j benefits from the number of homeless people already present in the same area. Thus the estimated coefficient of the stock of homeless people α captures the homeless network. The expected sign of α is positive.*

Second we examine the location choice of homeless people within different groups differently. Homeless people are divided into two groups from the viewpoint of a Kamagasaki *yoseba* where the day-labor market exists in Osaka City (OCUSG, 2001). The first group of homeless people had worked in the Kamagasaki *yoseba* and were willing to work in the Kamagasaki *yoseba*. The second group had not had work experience in the Kamagasaki *yoseba*. We refer to the first group as the *experienced Kamagasaki group* and to the second group as the *inexperienced Kamagasaki group*. To account for this, we estimate a fully interlinked model. The logit expression then becomes:

$$\mathrm{Pr}_{ij} = \frac{\exp[d_E(\alpha_E h_{ij} + \boldsymbol{x}'_{ij}\boldsymbol{\beta}_E) + d_I(\alpha_I h_{ij} + \boldsymbol{x}'_{ij}\boldsymbol{\beta}_I)]}{\sum_{j=1}^{J}\exp[d_E(\alpha_E h_{ij} + \boldsymbol{x}'_{ij}\boldsymbol{\beta}_E) + d_I(\alpha_I h_{ij} + \boldsymbol{x}'_{ij}\boldsymbol{\beta}_I)]}, \quad (2)$$

where subscript E (I) refers to the experienced (inexperienced) Kamagasaki group. The term d_E (d_I) is a dummy variable that takes the value 1, if homeless person i belongs to the experienced (inexperienced) Kamagasaki group, and 0 if he or she belongs to the inexperienced (experienced) Kamagasaki group.[7]

Again, as in Hypothesis 1, the positive α_E and α_I capture homeless networks. Eq. (2) shows that whether homeless networks affect the location of homeless people differs according to the viewpoint of the Kamagasaki *yoseba* . OCUSG (2001) has found that the geographic pattern of the two groups is different. Therefore, the following hypothesis is also examined.

Hypothesis 2 *The experienced Kamagasaki group and inexperienced Kamagasaki group prefer to locate in different places. Thus the estimated coefficients of spatial-specific attributes $\boldsymbol{\beta}_E$ and $\boldsymbol{\beta}_I$ will differ between the two groups.*

Note that the hypothesis related to peer and homed networks is discussed in Section 5.

3 Data

The main data employed in the estimation is the 1999 Interview Survey of Homeless People. In 1999, OCUSG (2001) collected microlevel data on 672 homeless individuals. These 672 homeless persons were each interviewed face-to-face over a period of one to two hours. The OCUSG (2001)

[7] Eq. (2) is equivalent to estimating the conditional logit model separately for each group.

survey asked homeless people to report the location and the year when they started to live in the reported place. To capture the effect of homeless networks on the location choice, we combine this data with the 1998 Homeless Count data.[8]

We use only those homeless people that started to live in the reported place after August 1998, because homeless people were counted in August 1998. This sample limitation implies that the location choice of homeless people depends on the number of homeless people already present in the area. The interview investigation was done for homeless living in public parks, on the street, and river banks in Osaka City. We exclude the sample of homeless people who live on the street and river banks, because the address is unclear. Note that locations of parks are converted into a census block. This is because almost all explanatory variables contain information by census block. Screening the data produces a sample of 12,802 ($346\times$ 37) observations, where 346 is the number of homeless individuals and 37 is the number of location choices. [9]

Table 1 presents summary statistics of the explanatory variables that are used in the estimation of Eq. (1). The number of preexisting homeless people in the census block j, HOMELESS, is the most important variable, because it captures the homeless network. We expect the coefficient of HOMELESS to be positive because of the homeless network (Hypothesis 1). We also include a quadratic specification of the number of homeless in the census block, HOMELESS^2, because the effect of social networks on the probability of choosing a location follows an inverted U-shaped pattern (Bauer, Epstein, and Gang, 2005).[10] The expected sign is negative. The negative sign may imply the negative competition effect on earnings. Almost 90% of homeless people in Osaka City collect discarded materials, especially corrugated cardboard and aluminum cans (OCUSG, 2001), in order to take them to a junk dealer to earn recycling income.[11] Usually, the quantity of recyclable items is constant in j. Increasing the number of homeless people reduces their earnings, and consequently generates a dispersion force.

[8] The OCUSG count of August 20–28, 1998, consisted of two components to avoid double counting. First, homeless people who slept in cardboard boxes, on benches, and slept without any cover, were counted on the nights of August 20–24. Second, those who lived in makeshift shacks made of cardboard or vinyl were counted in the days of August 24–28. This count revealed there were 8,660 homeless in Osaka City in 1998.

[9] A sampling number of homeless people in park j is highly correlated to the preexisting homeless population in j, i.e., the correlation coefficient is 0.97.

[10] In the estimation stage, we divide HOMELESS^2 by 100.

[11] In Japan, homeless people engage in begging in the street are very rare (Okamoto, 2007).

We include the size of park j, PARK SIZE, which is measured in units of 10 hectares, because a large-sized park will attract the homeless. Furthermore, we include DISTANCE, a Euclidean distance between the polycentric of Kamagasaki *yoseba* and the polycentric of the census block, which is measured in kilometers, because a Kamagasaki *yoseba* offers an employment opportunity for homeless people. Furthermore, free soup runs that are provided by volunteer groups, cheap food services, and SRO hotel services are concentrated in the Kamagasaki *yoseba* and their surroundings. Homeless people will choose to reside close to the business and commercial districts (Mizuuchi, 2003; Shima, 1999), because they search for a job after becoming homeless. Thus we include EMPLOYEE, the number of employees in the census block.

Spatial-specific characteristics also include PPL, the number of nighttime residential persons who work as production process workers or laborers in the census block. Note that production process laborers include construction workers and stevedores. OCUSG (2001) found that the majority of the day laborers who face the threat of becoming homeless are employed as construction workers or stevedores. We also incorporate POPULATION, the number of nighttime residential persons (except the number of residential persons that are production process laborers) in the census block. OCUSG (2001) found that friction between the homeless and neighboring residents is increasing because of the illegal occupation of a public park. OCUSG (2001) found that 20% of homeless people suffer from harassment by residents.

Lastly, we define WELFARE FACILITY, as the number of welfare facilities within 500 meters of the census block. Welfare facilities might offer a minimum standard of living, i.e., adequate social and health care services for homeless people.

Table 2 presents the mean of the explanatory variables that are used in the estimation for Eq. (2). The mean of HOMELESS is not different between the two groups, i.e., 223.7 for the experienced Kamagasaki group and 227.7 for the inexperienced Kamagasaki group. DISTANCE shows that the experienced Kamagasaki group chooses to reside close to the Kamagasaki *yoseba*, while the inexperienced Kamagasaki group settles about 1.5 km further away than them.[12]

[12] OCUSG (2001) also identified one more group, i.e., the group who had worked in the *yoseba* and were not willing to work in the *yoseba*. This group lives between the experienced Kamagasaki group and inexperienced Kamagasaki group from the Kamagasaki *yoseba*. We exclude this group from the sample, because the empirical results of the experienced Kamagasaki group and inexperienced Kamagasaki group are significantly different.

4 Estimation Results of Homeless Networks

The second column of Table 3 presents the estimation results for the conditional logit model using the full sample.[13] As expected, the number of preexisting homeless people in the block (HOMELESS) has a positive and significant coefficient in the location choice of homeless people. This implies that homeless networks exist in a homeless society. Hypothesis 1 is supported. We also find that HOMELESS^2 has a negative and significant coefficient. Thus the estimation results show that the effect of homeless networks on the probability of choosing a park follows an inverted U-shaped pattern.

To measure the intensity of homeless networks, we calculate the marginal effects of HOMELESS. The marginal effect of a change in some characterisitic (x^l_{ij}, where l is the column number of the element) of a park j on the probability that a homeless person i will choose to live in that park are given by the derivative of Eq. (1), i.e., $\partial \Pr_{ij} / \partial x^l_{ij} = \Pr_{ij}(1 - \Pr_{ij})\beta_l$, where β_l is the coefficient of x^l_{ij}. This marginal effect will vary with the characteristics of a park j, because it depends on $\Pr_{ij}$. Therefore, we calculate average marginal effect of a change in some characteristic x^l_{ij} on $\Pr_{ij}$, shown by Bauer, Epstein, and Gang (2005) and Jaeger (2007), i.e.,

$$\frac{\partial \Pr_{ij}}{\partial x^l_{ij}} = \frac{1}{37}\left(1 - \frac{1}{37}\right)\hat{\beta}_l,$$

where 37 is the number of location choices. Hence, to obtain the average marginal effects of HOMELESS, the estimated coefficients of HOMELESS reported in Table 2 are multiplied by the factor 0.026. Then we have 4.42×10^{-4}. Considering HOMELESS^2, the effect of the number of preexisting homeless people on the probability of choosing a particular park location peaks at approximately 283 people.

Park size has a statistically positive effect on the location choice of homeless people, i.e., more public space attracts homeless people. KAMAGASAKI has a positive and significant sign. Thus, homeless people prefer to settle far from the Kamagasaki *yoseba*. The other variables are insignificant, because the distribution of homelessness will differ between groups.

[13] We also estimate the conditional logit model with the density of EMPLOYEE, PPL, POPULATION, and WELFARE FACILITY (expect PARK SIZE and DISTANCE), because the census blocks vary in size and shape. There are, however, no significant differences from the results that are shown in Table 3. Thus they are not reported in the paper.

Next, columns 3 and 4 of Table 3 present the results for the conditional logit model for each group: experienced Kamagasaki group and non-Kamagasaki group. Before discussing the effect of homeless networks, we consider another control variable. Park-specific variable, PARK SIZE, has a positive sign. Both groups choose to live in large parks. The estimated coefficient of PARK SIZE in column 4 is significant at the 12% level.

Coefficients of spatial-specific attributes (DISTANCE, EMPLOYEE, PPL, POPULATION, WELFARE FACILITY) have opposite signs between the two groups. In the sama way as Bauer, Epstein, and Gang (2005), we employ the Wald test to test the null hypothesis of homoscedasticity; $\mathrm{H}_0 : \boldsymbol{\beta}_E = \boldsymbol{\beta}_I$, where subscript E (I) refers to the experienced (inexperienced) Kamagasaki group. As can be seen in the fifth column of Table 3, the null hypothesis was rejected in all five cases. Thus, Hypothesis 2 is supported.

Let consider the spatial-specific attributes of the experienced Kamagasaki group and the inexperienced Kamagasaki group, respectively. The experienced Kamagasaki group prefers to locate closer to the Kamagasaki *yoseba*. Labor recruiters go to the *yoseba* in the early morning, negotiate with day laborers, and take them to work sites. Thus, it is important for homeless people to reside close to the Kamagasaki *yoseba*, because they search for jobs there even after becoming homeless. The probability of choosing a certain park increases with respect to the nighttime population of production process laborers. This result reflects the fact that the experienced Kamagasaki group was employed as production process laborers (construction workers or stevedores) before they become homeless (OCUSG, 2001). They settle near the business and commercial districts where there are many employees, but stay away from residential suburbs where there is a large nighttime population. Ironically, the experienced Kamagasaki group does not choose to reside close to welfare facilities. This result suggest that welfare facilities have not functioned effectively to save experienced Kamagasaki group (Aoki, 2003; Okamoto, 2007; Suzuki, 2007).

Inexperienced Kamagasaki group prefer to locate far away from the Kamagasaki *yoseba*. They are less likely to choose parks where a large number of production process laborers exist. They settle near residential suburbs where there is a large nighttime population. These results may reflect the fact that the inexperienced Kamagasaki group was employed in the formal labor market before they became homeless (Aoki, 2003). Finally, they are more likely to choose a park close to a WELFARE FACILITY.

Again, the homeless network variable, the number of homeless people already present in the area, follows an inverted U-shaped pattern for the two groups. Hypothesis 1 is supported. On the one hand, the estimation results suggest that homed networks may operate in the experienced Kamagasaki group, because they settle near the *yoseba* where homed community (labor recruiters, cheap food services, soup-run services, flophouse markets) is concentrated. On the other hand, the estimation results suggest that peer networks may work in the inexperienced Kamagasaki group. The reason is twofold. First, they settle far from the *yoseba* where the link to homed community is strong. Secondly, they settle near the residential area where the probability of being harassed by residents is high. Therefore, they may help each other to survive from one day to the next. In the next section, however, we examine in more detail what kind of homeless networks exist in both groups.

To compare the intensity of homeless networks between two groups, we again calculate the marginal effects of HOMELESS. Following Bauer, Epstein, and Gang (2005) and Jaeger (2007), we have 3.38×10^{-4} for the experienced Kamagasaki group and 4.42×10^{-4} for the inexperienced Kamagasaki group, respectively. The effect of the number of preexisting homeless people on the probability of choosing a particular park location peaks at 325 people for the experienced Kamagasaki group, and 425 people for the inexperienced Kamagasaki group. These figures might imply that homeless networks appear to have a weaker effect on the experienced Kamagasaki group than the inexperienced Kamagasaki group. Furthermore, negative competition effects appear faster for the experienced Kamagasaki group than the inexperienced Kamagasaki group. However, the Wald test in the fifth column of Table 3, shows that homeless networks for the Kamagasaki group and the inexperienced Kamagasaki group are not statistically significantly different.

5 Peer Networks and Homed Networks

5.1 Empirical Model

In this section, we try to identify the effect of a peer network and a homed network on the location choice, separately. Peer networks refer to social ties between the homeless individual and members inside the homeless community. Homed networks refer to social ties between the homeless individual and members outside the homeless community (i.e., homed community). To capture these network effects on location choice, we add interaction terms of a personal attribute with the number of preexisting homeless people as follows:

$$\mathrm{Pr}_{ij} = \frac{\exp[(d_E(\alpha_E h_{ij} + \boldsymbol{x'}_{ij}\boldsymbol{\beta}_E + \boldsymbol{z}'_{ij}\boldsymbol{\gamma}_E h_{ij}) + d_I(\alpha_I h_{ij} + \boldsymbol{x'}_{ij}\boldsymbol{\beta}_I + \boldsymbol{z}'_{ij}\boldsymbol{\gamma}_I h_{ij})]}{\sum_{j=1}^{J}\exp[(d_E(\alpha_E h_{ij} + \boldsymbol{x'}_{ij}\boldsymbol{\beta}_E + \boldsymbol{z}'_{ij}\boldsymbol{\gamma}_E h_{ij}) + d_I(\alpha_I h_{ij} + \boldsymbol{x'}_{ij}\boldsymbol{\beta}_I + \boldsymbol{z}'_{ij}\boldsymbol{\gamma}_I h_{ij})]}, \qquad (3)$$

where $\boldsymbol{z}_{ij}$ is a vector of personal attributes of homeless person i, and $\boldsymbol{\gamma}_E$ and $\boldsymbol{\gamma}_I$ are a vector of coefficients. A positive (negative) sign of $\boldsymbol{\gamma}_E$ and $\boldsymbol{\gamma}_I$ imply that homeless people who have some personal attribute are more (less) geographically concentrated. Comparing these estimated coefficients allow us to test whether the different kinds of homeless networks exist between the two groups or not.

To determine what kind of homeless networks work in homeless societies, we design variables to measure a homed network and a peer network. To do this, interaction terms between a personal attribute and the number of preexisting homeless people are constructed as in Equation (3). We use two pieces of information: reasons for selection of the location and monthly income. The first piece of information is used to capture the homed network and peer network directly. The second piece of information, monthly income, is complementary in explaining both the homed network and the peer network.

Table 4 presents summary statistics of personal attributes that are used in the estimation of Eq. (3). Respondents were asked to choose the reasons for their location choice (multiple choice answer). There are the following six choices: the location is safe and sound, large, or provides shelter from the rain (ENVIRONMENT), the place provides water, is close to a toilet, close to a convenience store, or provides a soup run (LIVELIHOOD), the location is close to the Kamagasaki *yoseba*, or close to a junk dealer (WORK), the existence of peers in the location, or a large number of preexisting homeless people in the location (PEER), other reasons, and no reason. The peer network is captured by interaction terms of PEER with HOMELESS. To capture the homed network, we take the union of LIVELIHOOD and WORK (HOMED), because these two reasons may include social support (availability of soup run) and labor market. Therefore, interaction terms of HOMED with HOMELESS is a proxy variable to measure the impact of the homed network. We also take the union of ENVIRONMENT, other reasons, and no reasons (OTHERS is the reference reason).

The previous section suggested that homed networks work for the experienced Kamagasaki group, whereas peer networks work for the inexperienced Kamagasaki group. Therefore, the following hypothesis is examined.

Hypothesis 3 *The estimated coefficient of interaction terms of HOMELESS with HOMED will be positive for the experienced Kamagasaki group because of homed networks, and the estimated coefficient of interaction terms of HOMELESS with PEER will be positive for the inexperienced Kamagasaki group because of peer networks.*

Table 4 also presents summary statistics of monthly income (INCOME) that are used in the other specification.

5.2 Estimation Results of Peer and Homed Networks

Table 5 reports the estimation results from a specification for the stock of homeless population interacted with the reasons of location choice. We find that the impact of the homed network on location choice is significantly negative. The peer network is positive, but insignificant.

We find that the peer network is significantly positive for the inexperienced Kamagasaki group. Thus, Hypothesis 3 is supported. A positive sign implies that the existence of peers accelerates the geographic agglomeration of homeless people in a certain park for this group. Peers are important for survival, because they do not rely on the Kamagasaki *yoseba* (DISTANCE is significantly positive) and the homed network (HOMED$\times$HOMELESS is significantly negative). Peer networks are also important for protecting against harassment from residents, because they settle near the residential area.

On the other hand, the experienced Kamagasaki group is more likely to choose where homed networks exist, and less likely to choose where peer networks exist. Both of them, however, are insignificant. Thus, Hypothesis 3 is weakly supported for the experienced Kamagasaki group.

Wald tests ($H_0 : \gamma_E = \gamma_I$) show that both the peer network and the homed network have a heterogeneity impact on the location choice, because these networks work in the opposite direction.

The interaction terms of HOMELESS with INCOME are negative in all equations, but only significant in column 3 of Table 6. A significant negative sign indicates that the higher earning homeless people who rely on the Kamagasaki *yoseba* group are less geographically concentrated. They live apart from their peers when their income is high, because they are only weakly reliant on peers. Yamakita (2007) found from an interview survey that a voluntary income redistribution among homeless people exists in some homeless communities. An insignificant sign for the inexperienced Kamagasaki group may imply this, because this group is more likely to depend on peers.

6 Conclusion

This paper considers the location choice of homeless people by focusing on homeless networks in Osaka City. To capture the effect of homeless networks, we examine the relation between the location choice of homeless individuals in a certain park and the number of homeless people already present in the same area. Using a conditional logit model, the empirical results show the presence of homeless networks. This implies that the homeless network is one factor in homelessness agglomeration in Osaka City.

Furthermore, important differences in location-choice behavior are observed when we divide the samples into two groups: experienced and inexperienced Kamagasaki groups. On the one hand, peer networks that provide a social tie between the homeless individual and members of the homeless community are observed in the inexperienced Kamagasaki group. Peers are important for survival because they do not rely on the Kamagasaki *yoseba* where labor recruiters provide information on daily employment and volunteer groups provide soup runs for homeless people. Peers are also important for protection against harassment from residents, because they settle near residential areas. Therefore, peer networks may create geographic concentrations of the inexperienced Kamagasaki group far from the Kamagasaki *yoseba*. Homeless people who belong to this group do not disperse even when their income is high, because a high-income homeless person may share the money with a low-income homeless person.

On the other hand, homed networks that provide an external link between the homeless individual and members of the homed community are observed in the experienced Kamagasaki group, but to an insignificant extent. The experienced Kamagasaki group settle close to the Kamagasaki *yoseba* where homed communities are concentrated. Thus, homed networks might create geographic concentrations of the experienced Kamagasaki group around the Kamagasaki *yoseba*. Furthermore, we find that the higher earning homeless people in this group are less geographically concentrated. The dispersion force appears faster for the higher earning homeless individuals, because they are not reliant on peers.

Our empirical results criticize the city government policy that has been implemented since the late 1990s. The city government has evicted and dispersed homeless people, because neighboring residents and business people suffer a negative externality from the presence of homelessness. This dispersion policy, however, threatens the life of homeless people further, because both the experienced Kamagasaki and inexperienced Kamagasaki groups benefit from homeless networks.

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Table 1

Summary Statistics of Variables

Variable	Mean	SD	Min	Max	Source
HOMELESS (people)	226.00	144.52	2	424	HCD
PARK SIZE (10 ha)	4.65	4.23	0.03	10.50	GIS
DISTANCE (kilometers)	4.06	1.85	0.78	10.06	GIS
EMPLOYEE (1000 people)	0.83	1.28	0.02	8.19	EEC
PPL (1000 people)	0.48	0.11	0	0.10	PC
POPULATION (1000 people)	0.77	1.33	0.06	16.623	PC
WELFARE FACILITY (#)	0.15	0.35	0	2	GIS
Number of Obs.			346		IHSP

HCD: 1998 Homeless Count data.

EEC: 2001 Establishment and Enterprise Census.

PC: 2000 Population Census.

IHSP: 1999 Interview Survey of Homeless People.

Table 2

Mean of Variables for Experienced and Inexperienced Kamagasaki Groups

Variable	Experienced	Inexperienced	Source
HOMELESS (people)	223.69	227.73	HCD
PARK SIZE (10 ha)	3.82	5.27	GIS
DISTANCE (kilometers)	3.22	4.69	GIS
EMPLOYEE (1000 people)	1.01	0.70	EEC
PPL (1000 people)	0.06	0.04	PC
POPULATION (1000 people)	0.73	0.81	PC
WELFARE FACILITY (#)	0.11	0.19	GIS
Number of Obs.	148	198	IHSP

HCD: 1998 Homeless Count data.

EEC: 2001 Establishment and Enterprise Census.

PC: 2000 Population Census.

IHSP: 1999 Interview Survey of Homeless People.

Table 3

Conditional Logit Estimates for Homeless Networks

	All	Experienced	Inexperienced	Wald test
HOMELESS	0.017 ***	0.013 ***	0.017 ***	0.87
	(0.002)	(0.003)	(0.003)	
$HOMELESS^2 \div 100$	-0.003 ***	-0.002 ***	-0.002 ***	0.08
	(0.0004)	(0.0007)	(0.0007)	
PARK SIZE	0.091 ***	0.225 ***	0.064 +	5.27 **
	(0.030)	(0.057)	(0.041)	
DISTANCE	0.120 ***	-0.225 ***	0.305 ***	31.65 ***
	(0.036)	(0.081)	(0.048)	
EMPLOYEE	-0.020	0.168 **	-0.138 +	7.91 ***
	(0.054)	(0.068)	(0.085)	
PPL	-0.688	6.705 **	-5.032 **	10.20 ***
	(1.500)	(2.918)	(2.234)	
POPULATION	-0.033	-0.794 **	0.237 +	6.17 **
	(0.116)	(0.388)	(0.147)	
WELFARE FACILITY	0.139	-0.503 *	0.445 **	7.86 ***
	(0.152)	(0.258)	(0.218)	
Pseudo R^2	0.261	0.291		

Standard deviation in parentheses

*** indicates significant at 1%

** indicates significant at 5%

* indicates significant at 10%

+ indicates significant at 12%

The Wald test statistics concern the differences in the relevant pair of coefficient estimates presented in columns 3 and 4. The test statistics have a chi-squared distribution with one degree of freedom.

Table 4

Personal Attributes of Homeless People: Reasons for Determination of Location and Monthly Income

Variable	All	Experienced	Inexperienced
Reasons for determination of the location			
PEER (%)	33.5	34.0	33.2
HOMED (%)	38.5	32.6	42.9
OTHERS (%)	70.3	70.8	69.9
Number of Obs.	340	144	196
Monthly income			
INCOME (10,000yen)	3.24	3.19	3.29
Number of Obs.	230	111	119

Table 5

Conditional Logit Estimates for Homeless Networks: Peer and Homed Networks Interactions

	All		Experienced		Inexperienced		Wald test	
HOMELESS	0.018	***	0.013	***	0.019	***	1.79	
	(0.002)		(0.003)		(0.003)			
$HOMELESS^2 \div 100$	-0.003	***	-0.002	***	-0.003	***	0.52	
	(0.0004)		(0.0007)		(0.0007)			
PARK SIZE	0. 090	***	0.215	***	0.070	*	4.20	**
	(0.030)		(0.057)		(0.041)			
DISTANCE	0.122	***	-0.220	***	0.304	***	30.97	***
	(0.036)		(0.081)		(0.048)			
EMPLOYEE	-0.022		0.165	**	-0.140	+	7.80	***
	(0.054)		(0.068)		(0.085)			
PPL	-1.026		5.949	**	-4.968	**	8.69	***
	(1.522)		(2.953)		(2.234)			
POPULATION	-0.012		-0.730	*	0.234	+	5.39	**
	(0.116)		(0.388)		(0.147)			
WELFARE FACILITY	0.141		-0.482	*	0.436	**	7.39	***
	(0.152)		(0.258)		(0.218)			
HOMELESS × PEER	0.001		-0.001		0.003	**	6.26	**
	(0.001)		(0.001)		(0.001)			
HOMELESS × HOMED	-0.002	***	0.0002		-0.004	***	6.51	**
	(0.001)		(0.001)		(0.001)			
Pseudo R^2	0.261			0.297				

Standard deviation in parentheses

*** indicates significant at 1%

** indicates significant at 5%

* indicates significant at 10%

+ indicates significant at 12%

The Wald test statistics concern the differences in the relevant pair of coefficient estimates presented in columns 3 and 4. The test statistics have a chi-squared distribution with one degree of freedom.

Table 6

Conditional Logit Estimates for Homeless Networks: Income Interactions

	All		Experienced		Inexperienced		Wald tset	
HOMELESS	0.019	***	0.014	***	0.020	***	1.30	
	(0.002)		(0.004)		(0.004)			
$HOMELESS^2 \div 100$	-0.003	***	-0.002	***	-0.004	***	1.43	
	(0.0005)		(0.0007)		(0.001)			
PARK SIZE	0.103	***	0.205	***	0.118	**	0.96	
	(0.037)		(0.065)		(0.060)			
DISTANCE	0.067		-0.233	***	0.253	***	20.15	***
	(0.044)		(0.091)		(0.059)			
EMPLOYEE	-0.012		0.146	*	-0.123		4.22	**
	(0.064)		(0.080)		(0.103)			
PPL	0.346		7.200	**	-3.332		6.42	**
	(1.691)		(3.238)		(2.604)			
POPULATION	-0.058		-0.867	**	0.180		5.08	**
	(0.124)		(0.434)		(0.165)			
WELFARE FACILITY	0.090		-0.414		0.358		4.22	**
	(0.175)		(0.269)		(0.262)			
HOMELESS × INCOME	-0.0002		-0.0004	*	-0.0001		1.07	
	(0.0001)		(0.0002)		(0.0002)			
Pseudo R^2	0.261				0.261			

Standard deviation in parentheses

*** indicates significant at 1%

** indicates significant at 5%

* indicates significant at 10%

+ indicates significant at 12%

The Wald test statistics concern the differences in the relevant pair of coefficient estimates presented in columns 3 and 4. The test statistics have a chi-squared distribution with one degree of freedom.