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Are rural residents willing to trade-off higher noise for lower air pollution? Evidence from revealed preferences

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ABSTRACT

The rise in urbanization has led to an expansion of traditional urban externalities toward suburban and rural areas together with changes in the preferences of human populations for noise and air pollution. This paper analyses the preferences of the population living in rural, suburban and urban areas for noise and air pollution utilizing a revealed preference approach. Data on actual choices of residential location are analysed utilizing a Latent Class Discrete Choice model that raises two different groups of residents with different preferences for air and noise pollution. As expected and confirmed by the Multinomial and Mixed Logit models, the first group of the Latent Class model accepts higher levels of noise and air pollution in urban than in suburban and rural areas. However, the second group of residents have preferences for higher levels of noise and lower levels of air pollution in rural and suburban than in urban areas. Thus, results show some rural residents are willing to trade higher levels of noise for lower levels of air pollution, indicating adaptation of preferences to a lower level of the traditional tranquillity enjoyed in less densely populated rural areas.

1. Introduction

The expansion of urbanization is transforming the adjacent natural environments and causing external effects on the suburban and rural areas (Beilin et al., 2014; Ma et al., 2018). Noise and air pollution are two of the most important nuisances caused by urban development. These external effects lead to large damages to the quality of live of human populations that could be tackled by planning policies (Stansfeld, 2015; Schaeffer et al., 2016). The exposure to noise can cause psychological damages and heart conditions (Jariwala et al., 2017; Carey et al., 2018) while high levels of air pollution have been linked to earlier mortality and chronic respiratory conditions (Hankey and Marshall, 2017; Manisalidis et al., 2020).

Individuals reveal their preferences for noise and air pollution by choosing their residential and working locations (Schaeffer et al., 2016; Von Graevenitz, 2018). This paper contributes to the literature first by analysing the role of noise and air pollution in the choice of residential location between rural and urban areas, and second by utilizing a residential choice model based on revealed preference or market data. The joint impact of these externalities on rural residential choice has not been earlier investigated with a residential demand modelling approach (Schirmer et al., 2014; Chiarazzo et al., 2014; Chiarini et al., 2020). Previous approximations to the impact of air and noise pollution on residential property markets utilize the hedonic price model and focus on urban areas where these externalities are more salient (Nelson, 1982; Le Boennec and Salladarré, 2017). However, noise and air pollution are increasing in rural and suburban environments (Casey et al., 2017; Tong and Kang, 2020; Schwela, 2021).

The demand of residential location is commonly analysed utilizing discrete choice models (McFadden, 1978). In this paper we utilize a latent class model that considers the underlying heterogeneity across the population of residents (McFadden and Train, 2000). Latent class models have been utilized in other areas of transportation and environmental sciences, but there are only few applications in the context of residential location choice utilizing both stated preference surveys (Liao et al., 2015; Walker and Li, 2007; Olaru et al., 2011; Ibraimovic and

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Hess, 2018) and revealed preference data (Ardeshiri and Vij, 2019; Lee et al., 2019; Paleti et al., 2020).

Although latent class models provide insights on the sources of heterogeneous preferences across householders (Hess et al., 2008), previous studies have not controlled for the role of key environmental variables, such as the levels of noise and air quality, on the choice of residential location. These variables are increasingly relevant in the decision of residential location as society's preferences evolve toward higher levels of quality of life and sustainability (Chiarini et al., 2020), and therefore may lead to heterogeneous preferences for residential location.

The evidence is obtained in Spain, a country that has experienced a transformation of rural environments because of the process of urbanization (Le Gallo and Chasco, 2008; García and Hernández, 2008; García and Raya, 2011; Barbero-Sierra et al., 2013; González and Ortega, 2013; Cardesin Diaz and Araujo, 2017; de Andrés et al., 2017). The data comes from official statistics of a large household residential survey across different areas of population density (urban, suburban and rural). Thus, the data is based on real or revealed preference choices that citizens have made for their location of residence, and therefore have the advantage of not being subject to the potential biases from answers to questions of hypothetical behaviour such as in stated choice experiments (Walker and Li, 2007; Liao et al., 2015). The results with the the latent class model show that there are various preferences for rural and urban areas, with a class of households that are willing to trade higher levels of noise for lower levels of air pollution while enjoying the attributes of rural areas.

2. Literature review

2.1. Air pollution, noise and residential choice

The choice of residential location is influenced by environmental amenities and reflected in market prices. Most of the literature assessing the effects of environmental attributes of residential location on property prices follows the hedonic market approach (Nelson, 1982; Chiarazzo et al., 2014; Von Graevenitz, 2018). That is, property prices are the result of the interaction of demand and supply of household residences (Rosen, 1974), and therefore are affected by the variables that influence the choice of residential location (Munroe, 2007; Freeman et al., 2019). The levels of environmental parameters defining various elements of environmental quality such as noise and air quality are relevant factors explaining property prices and residential choice (Blanco and Flindell, 2011; Szczepańska et al., 2015; Schaeffer et al., 2016).

Most empirical studies focus on the impact of noise and air pollution separately on property prices, and there are only a few studies that consider them together (Le Boennec and Salladarré, 2017). Empirical evidence shows a negative effect of noise and air pollution on property prices (Smith and Huang, 1993; Chang and Kim, 2013). Le Boennec and Salladarré (2017) found that despite air pollution was influenced by the location attributes of housing in Nantes (France), its levels did not show any influence on housing prices. However, noise pollution was affected by the location of houses and simultaneously exerted a significant influence on housing prices.

Studies on migration have shown that migrants are attracted by environmental amenities and avoid negative locational externalities (Bayer et al., 2009). The environmental factors are relevant for particular population groups such as retirees (Duncombe et al., 2001; Park and Kim, 2016; Lu, 2020; Grout et al., 2016; Qin and Liao, 2016), members of the creative class (McGranahan et al., 2011) or higher income households (Bayoh et al., 2006). In California, Banzhaf and Walsh (2008) found that high air pollution in some communities led to emigration of rich households and immigration of poorer households.

The perceptions of noise and air pollution have been shown to be a fairly good approximation to the objective measures of these externalities (Chiarini et al., 2020). In addition, subjective perceptions held by individuals and social groups reflect the social and personal dimensions of the externality, and may have a higher impact on the quality of life and market decisions than the objective indicators (King, 2015; Loschiavo, 2019; Navarro et al., 2020). Chasco and Gallo (2013) found that house prices in the city of Madrid were better explained by subjective evaluations of pollution and noise than by variables gathered on monitoring stations. Thus, the utilization of objective indicators of noise and air pollution does not provide better statistical results than recurring to subjective indicators in explaining residential property prices (Cordera et al., 2019). Similarly, Von Szombathely et al. (2018) showed that the annoyance caused by traffic noise is clearly related to noise emissions in urban areas in Hamburg, while Verbeek (2018) found a weak correlation between objective and subjective measurements of exposure to noise in Ghent, Belgium. On the other hand, Chiarini et al. (2020) developed a subjective combined indicator of noise and air pollution, finding that households' perceptions of environmental quality are strongly heterogeneous in urban, suburban and rural areas.

2.2. Rural versus urban residential choice

The choice of rural vs. urban residential locations can be influenced by socioeconomic, dwelling, infrastructure and landscape considerations (Schirmer et al., 2014; Meen, 2016; Ströbele and Hunziker, 2017; Flambard, 2017). Rural settlements are associated with lower levels of population density, and a different typology of housing, infrastructure and economic activities than those predominating in the urban and suburban settings (van Dam et al., 2002; Lotfi et al., 2019). Based on stated preference moving intentions, Kim et al. (2005) found that people have a preference for lower density locations, but Bhat et al. (2013) found that households generally prefer to locate in medium-density neighbourhoods based on revealed preference data.

However, the impact of population density on residential choice varies according to the sociological profile (e.g. income, age, wealth, family status, life stage, lifestyle) and the size of the household (Feijten et al., 2008; Galster et al., 2010; Blumenberg et al., 2019). The lower density of rural and suburban areas are preferred by larger households (Zondag and Pieters, 2005; Guo and Bhat, 2007), and by those with personal characteristics as seniors (Park and Kim, 2016; Marois et al., 2018; Marois et al., 2019), high income (Guo and Bhat, 2007; Bhat et al., 2013), and children (Bhat et al., 2013). High density or urban areas have been found preferred by younger generations (Lee, 2020), and lower income households (Bhat et al., 2013; Ardeshiri and Vij, 2019).

2.3. Latent class residential choice

Most applications of latent class models to residential choice utilize stated preference data of discrete choice experiments, which are based on asking respondents hypothetical choice questions incorporated into designed survey instruments. For instance, Walker and Li (2007) found three different classes according to the preferences for household density and transport mobility. Olaru et al. (2011) identified two classes depending on the preferences for proximity to transportation facilities and environmental quality while Smith and Olaru (2013) found four classes according to different lifestyles. Liao et al. (2015) identified two groups with stated preference data, depending on the preferences for mixed housing types and the proximity to work, public transit, shops and restaurants.

The studies based on a revealed preference approach are based on census data or household surveys of individual records about their place of residence and mobility of residence. Lee et al. (2019) modelled the residential choice of Millennials and the members of Generation X, showing that there were three classes of individuals according to their preferences for urban or suburban lifestyles, facilities and amenities. Ardeshiri and Vij (2019) considered the simultaneous choice of neighbourhood and transport mode, finding six-household classes that differ in terms of their lifestyle preferences involving neighbourhood attributes and household characteristics. Similarly, Paleti et al. (2020) analysed joint residential and work location choices showing that there was significant heterogeneity in the probability of different neighbourhood alternatives (urban, suburban, rural), and that the latent class model outperformed the standard MNL models.

3. Modelling

The choice of residential location can be represented as a discrete decision between alternatives defined by their attributes that include the characteristics residence and the environment surrounding it (McFadden, 1978; McFadden and Train, 2000). The individual chooses the place of residence taking into account the values of the different attributes that define the housing alternatives, and considering her individual or family socioeconomic characteristics. In the latent class (LC) discrete choice model (McFadden and Train, 2000; Greene and Hensher, 2003) preference heterogeneity is accounted for by a discrete distribution over unobservable endogenous (latent) classes of residents. Preferences are assumed to be homogeneous within each class but are allowed to differ across classes of residents.

Considering a random utility model based on alternative specific constants for the residential locations (Train, 2009; Paleti et al., 2020; Nickkar et al., 2020), the utility that household i who belongs to segment s derives from alternative residential location $j \in$ J locations is given by

$$U_{ij/s} = \lambda_{js} X_{ij} + \varepsilon_{ij/s} \tag{1}$$

where X_{ij} is the vector of characteristics of the household (e.g. noise and air pollution perceptions, income and house attributes) interacted with the alternatives j, i.e. $X_{ij} = \gamma_j{*}K_{ij}$ -where K_{ij} is the vector of household's characteristics choosing alternative j and γ_j is an indicator variable $\gamma_j = 1$ for alternatives $j = 1, \ldots,$ J-1 respectively; λ_{js} is a vector of parameters for household characteristics on segment s for alternative j, and$\varepsilon_{ij|s}$is the random component of utility for each segment of residents which is assumed to be identically and independently standard Gumbel distributed. Thus, the probability that alternative location j is selected by resident i belonging to segment s is given by:

$$P_{ij/s} = \frac{exp\lambda_{js}X_{ij}}{\sum_h exp\lambda_{hs}X_{ih}} \tag{2}$$

Membership to a specific segment of households is determined by a likelihood function M that classifies individuals in one of the segments with probabilityP_{is}. The membership function is given by $M_{is} = a_s Z_i + \xi_{is}$ where Z_i is a vector of socio-economic and other observed characteristics of the household and ξ_{is} is an error term. Assuming that this error term is also *iid* and follows a type 1 extreme value distribution, the probability that a household i belongs to segment s is given by

$$P_{is} = \frac{exp(a_s Z_i)}{\sum_s exp(a_s Z_i)} \tag{3}$$

The joint probability that household i belongs to segment s and chooses residential location alternative j is given by

$$P_{ijs} = \left(P_{ij/s}\right){*}\left(P_{is}\right) = \left[\frac{exp\lambda_{js}X_{ij}}{\sum_h exp\lambda_{hs}X_{ih}}\right]{*}\left[\frac{exp(a_s Z_i)}{\sum_s exp(a_s Z_i)}\right] \tag{4}$$

The alternative specific LC model is a special case of the mixed logit (ML) model that accounts for random parameter in the specification of the utility function where the parameter distributions are discrete (instead of continuous). For the alternative specific ML model the utility function is defined as

$$U_{ij} = (\lambda_j + \eta_i) X_{ij} + \varepsilon_{ij} \tag{5}$$

where λ_j represents the mean value of the households' preferences across the population and η_i is the deviation from the mean of the preferences for household i. Thus, parameters λ_j follow a continuous distribution f with mean λ and covariance matrix Ω_β. The probability of choosing alternative residential location i is

$$P_{ij} = \int \frac{exp(\lambda_j + \eta_i) X_{ij}}{\sum_h exp(\lambda_h + \eta_i) X_{ih}} f(\lambda) d(\lambda) \tag{6}$$

For comparison purposes, the multinomial logit model (MNL) has also been widely utilized in residential location demand analysis. This is the workhorse model in discrete choice that considers that the parameters of the utility function are fixed and not random i.e. $\eta_i = 0$, and therefore do not allow for the consideration of preference heterogeneity.

4. Data

The discrete choice models are applied to explain the choice of residential housing in Spain according to the type of area: urban, suburban and rural. The urban concentration has involved the abandonment of rural areas and the growth of larger municipalities (Gómez-Antonio et al., 2016). The objective is to determine how the individual characteristics and attributes of the area, e.g. pollution and noise, affect the choice of the area of residence, as well as to evaluate the existence of groups or classes of preferences in the choice of residence.

The database is obtained from the 2019 Living Conditions Survey (LCS) of the National Statistics Institute of Spain, which includes observations from 15,887 households. The data reveal preferences about the choice of housing by Spanish families according to household characteristics. The LCS is an annual statistical operation aimed at households carried out in all the countries of the European Union. The LCS is the source of the European Union Statistics on Income and Living Conditions (EU-SILC) of Spain that collects cross-sectional microdata on income and living conditions, and produces quality reports for Eurostat.

Table 1 presents the definition of the variables describing the three alternative zones and Table 2 shows the summary statistics. The number of households for each of the categories is 7711, 3666 and 4510 respectively. The population under study are the people residing in Spain who are members of private households living in family dwellings, as well as those households. Recorded socioeconomic characteristics are those of the head of the household responding the survey. In 2019, the household non-response rate was 36.7%, and the individual non-response rate was 1.44%.

The LCS for Spain follows Eurostat's guidelines in classifying all the territory of the country into three different areas according to the number of inhabitants per square km and the total population living in

Table 1
Definition of the variables.

Variable	Definition
NOISE	Equals 1 if the household is affected by noise coming from neighbours or outside (traffic, businesses, industry, etc); 0 in any other case.
AIR POLLUTION	Equals 1 if the household is affected by air pollution coming from traffic or industry; 0 in any other case.
DELINQUENCY	Equals 1 if the household is affected by problems of delinquency nearby; 0 in any other case.
CONDOMINIUM	Equals 1 if the house is in a condominium; 0 in any other case (single house).
NUMBER OF ROOMS	Equals 1 if the number of bedrooms of the house is 5 or more, 0 otherwise.
INCOME	Total disposable household income in Euros.
SINCOME	Equals 1 if household total disposable income is above the median, i.e. 24,854 €/year; *0* in any other case.
AGE	Number of years of age of the householder.
MARRIED	Equals 1if the householder is married; 0 in any other case.
CHILDREN	Equals 1 for households with children that are economically dependent; 0 in any other case.
HOUSEHOLD SIZE	Equals 1 if the household has between 1 and 3 members; 0 in any other case, i.e. between 4 and 13 members.
NATIVE	Equals 1 if the householder has Spanish nationality; 0 in any other case.

Table 2
Descriptive statistics (standard errors in brackets).

Variable	Zone 1	Zone 2	Zone 3
NOISE	0.19	0.11	0.07
	(0.39)	(0.31)	(0.25)
AIR POLLUTION	0.15	0.06	0.04
	(0.35)	(0.23)	(0.19)
DELINC	0.16	0.07	0.06
	(0.36)	(0.25)	(0.24)
CONDOMINIUM	0.85	0.62	0.31
	(0.35)	(0.48)	(0.46)
NUMBER OF ROOMS	0.56	0.64	0.71
	(0.497)	(0.480)	(0.45)
INCOME	32,141.84	28,795.28	25,590.11
	(24,325.06)	(19,593.54)	(17,353.04)
S_INCOME	0.54	0.50	0.42
	(0.49)	(0.50)	(0.49)
AGE	58.31	56.89	59.81
	(155.48	(150.78)	(155.40)
MARRIED	0.54	0.59	0.59
	(0.49)	(0.49)	(0.49)
CHILDREN	0.33	0.37	0.32
	(0.47)	(0.48)	(0.46)
HOUSEHOLD SIZE	0.77	0.73	0.76
	(0.41)	(0.43)	(0.42)
NATIVE	0.89	0.88	0.94
	(0.31)	(0.33)	(0.24)
Observations	7.711	3.666	4.510

Source: Elaboration based on LCS_2019 (EU_SILC).

the area. The data for the dependent variable comes from the classification of the location of the household according to the degree of urbanization into three different levels (European Commission, 2020, pp. 112): i) densely populated zones, ii) intermediate or medium density zones, and iii) thinly populated zones. Urban and suburban areas are reflected in densely and intermediate populated zones which are defined as continuous grid cells of 1km^2 with a density of at least 500 and 300 inhabitants per km^2 respectively, and with a minimum population of 50,000 and 5000 respectively. The rest of the areas in the country are classified as rural zones or thinly populated areas.

The density indicator is utilized in the development of the data base as a proxy for the characterization of the three alternative areas which embed more indicators that may be correlated with density, such as accessibility, physical and social distances, commerce and culture. Because of the ordered nature of the density indicator, an ordered response model may be utilized to explore the preferences for alternative levels of density (Bhat and Guo, 2007). However, the discrete choice modelling better represents the consumer as choosing between alternative residential locations involving different environments and characteristics.

5. Estimation results

5.1. Model selection and results for MNL and ML

Table 3 presents the estimation results of the models of residential location according to the level of density of housing areas. The dependent choice variable is modelled in three alternative levels as defined by Eurostat: urban zone for the densely populated areas, suburban zone for the intermediate areas, and rural zone for the thinly populated areas.

Heterogeneity in the ML is incorporated by specifying random parameters for the socioeconomic variables of income, civil status and children in the household. The distributions of the random parameters were specified as normal, and there were no significant differences in the model fit statistics when other alternative non-negative distributions were adopted, i.e. lognormal or truncated normal (Mariel et al., 2021). In the latent class model, the best fit is represented by a two classes model that represents two types of dwellers defined by different characteristics and preferences about their choice of type of density area.

Table 3
Estimation results of Mixed Logit and Latent Class models.

Attributes	MNL	ML	LC	
			Class 1	Class 2
Environmental attributes				
NOISE _S	−0.121	- 0.096	1.81***	- 0.371***
	(1.74)	(1.38)	(−5.62)	(4.35)
NOISE_R	−0.360***	- 0.379***	0.95***	- 0.438***
	(4.37)	(4.15)	(−3.52)	(4.82)
AIR POLLUTION_S	−0.339***	- 0.316***	−1.32***	- 0.304**
	(3.54)	(3.50)	(4.78)	(2.91)
AIR POLLUTION_R	−0.558***	- 0.555***	−2.93***	- 0.461***
	(4.88)	(4.71)	(4.17)	(3.88)
DELINQUENCY_S	−0.730***	- 0.673**	−1.27***	- 0.914***
	(7.90)	(7.76)	(−5.21)	(8.69)
DELINQUENCY_R	−1.151***	- 1.192***	−2.03***	- 1.174***
	(10.64)	(10.53)	(3.37)	(10.45)
House characteristics				
CONDOMINIUM_S	−1.496***	−1.542***	−4.10***	−1.803***
	(−23.50)	(−25.33)	(−5.01)	(−24.40)
CONDOMINIUM_R	−2.973***	−3.308***	−3.77***	−3.281***
	(−43.27)	(−33.31)	(−5.86)	(−40.48)
NUMBER OF ROOMS_S	0.1446**	0.164**	2.27***	0.032
	(2.60)	(2.98)	(5.47)	(0.54)
NUMBER OF ROOMS_R		0.280***	1.55***	0.258***
		(3.70)	(5.09)	(3.48)
Socioeconomics				
SINCOME_S	−0.348***	−0.378***	−4.36***	−0.362***
	(−7.02)	(−7.52)	(−5.28)	(−6.58)
SINCOME_R	−0.719***	−0.885***	−1.32***	−0.772***
	(−13.61)	(−10.87)	(−3.45)	(−12.93)
AGE_S	−0.011***	−0.012***	2.52***	−0.020***
	(−6.47)	(−8.61)	(5.70)	(−11.41)
AGE_R	−0.010***	−0.012***	4.33***	−0.021***
	(−5.67)	(−7.35)	(5.86)	(−10.89)
MARRIED_S	0.250***	0.230***	−0.55***	0.433***
	(4.84)	(4.42)	(−5.67)	(7.27)
MARRIED_R	0.260***	0.230***	−1.09***	0.409***
	(4.79)	(3.37)	(−4.73)	(6.55)
CHILDREN_S	0.096 (1.45)	0.022 (0.37)	−1.02***	0.0542
			(−3.65)	(0.83)
CHILDREN_R	−0.010	−0.252**	1.19***	−0.078
	(−0.14)	(−2.68)	(3.47)	(−1.07)
HOUSEHOLD SIZE_S	−0.003	−0.055	0.54***	−0.077
	(−0.05)	(−0.86)	(3.03)	(−1.08)
HOUSEHOLD SIZE_R	0.025 (0.34)	−0.063	−1.06**	−0.039
		(−0.77)	(−2.33)	(−0.49)
NATIVE_S	0.154 (1.95)	0.111 (1.46)	−1.92***	0.368***
			(−5.47)	(4.29)
NATIVE_R	0.372***	0.390***	−1.65***	1.079***
	(4.03)	(3.92)	(−6.15)	(8.49)
Standard deviations				
INCOME_R		0.736***		
		(3.39)		
MARRIED_R		0.578**		
		(2.44)		
CHILDREN_R		1.137***		
		(6.44)		
Class membership equation				
SINCOME				0.211***
				(2.93)
AGE				−0.143***
				(3.05)
CONDOMINIUM				2.074**
				(2.10)
Class share			34%	66%
Log-likelihood	−14,169.22	−14,086.01	−14,015.03	
Pseudo R^2	0.202	0.218	0.253	
AIC	28,382.45	28,291,05	28,226.03	
BIC	28,575.08	28,514.78	28,463.04	
Obs.	15,635	15,635	15,635	

(t-stats in parenthesis) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Reference alternative: Urban Zone (U) for alternatives Suburban (S) and Rural (R)

Model fit is satisfactory, and the model with latent classes outperforms the MNL and ML models according to the statistics of goodness of fit. Table 4 presents the statistics of the goodness of fit for the different number of classes of the latent class model with the model with one class (or no classes) represented by the MNL model. The best model is given by the model with two classes since it is the one with the lowest value of the AIC and BIC statistics. Therefore, this model with two alternative classes is chosen for comparison with the MNL and ML models.

Results for the MNL and ML are similar en terms of the significance of the variables explaining residential choice according to location density. The parameter of noise pollution is not significant for the suburban demand (NOISE_S), implying that there are no differences in the choice probability of suburban areas with respect to the urban demand in the perception of noise. However, the parameter is negative and significant at the 0.001 level for the alternative of rural housing (NOISE_R), meaning that those subjects perceiving lower levels of noise pollution have a preference for living in the rural areas as opposed to the alternative urban and suburban areas.

Air pollution (AIR) is negative and significant at the 0.001 level for both alternatives of choice of density areas. Thus, the probability of choosing suburban or rural areas rises for those households perceiving less air pollution. Since the parameter is larger for households in the rural areas than for those in the suburban areas, the probability of living in a rural area is higher the lower the level of air pollution perception of the household. The difference in the estimated parameter values of air pollution between the alternative areas indicates that the probability of living in a rural area is much higher than in the suburban area for those households facing lower air pollution.

5.2. Latent class results

The results of the latent class model confirm most of the predictions of the MNL and ML models but lead to two alternative classes of households characterized by different preferences for the environmental attributes and the housing characteristics. The parameters of class 2 are quite similar to those obtained with the MNL and ML models, thereby showing a moderate preference of households in the less dense suburban and rural areas for the environmental attributes and the house characteristics with respect to the baseline urban area. However, individuals in class 1 show higher values of the parameters of the explanatory variables, indicating a strong preference for the environmental attributes and household characteristics, as well as overall higher impacts of the socioeconomic characteristics on the choice of suburban and rural areas.

Regarding the environmental attributes, the preferences of class 1 about noise pollution are reversed with respect to those obtained from class 2, since the parameters of NOISE are positive for both alternatives of less dense residential areas –i.e. suburban and rural areas. The parameter value of NOISE is much smaller in absolute terms for the rural area than for the suburban area, thereby indicating that although in both alternative areas households accept a higher level of noise pollution, the probability of noise is higher for the suburban than for the rural level.

In the case of air pollution, the parameters of AIR POLLUTION for class 1 are both negative and of higher values than for class 2, showing a higher preference for lower levels of air pollution for the former class. The parameter values in both classes are also higher for rural areas than for the suburban areas. Thus, class 2 is clearly characterized by a lower preference for air quality but a higher preference for quietness than class 1 when it comes to choose the alternatives of the less dense suburban and rural areas over the more polluted urban areas.

Subjects in class 1 have stronger preferences for a type of housing involving detached or individual houses than those in class 2, both for the suburban and rural areas, as can be seen by the negative signs of the parameter of the variable CONDOMINIUM. This parameter is larger for the alternative of rural areas than for the alternative of suburban areas in both classes, although the largest value is obtained for the rural areas in class 1. In addition, the size of the household (HOUSEHOLD SIZE) is significant only for class 1, thereby showing that for class 1 those households with more individuals are more likely to live in rural areas, whereas for class 2 there is no difference in the size of the household with respect to the urban areas.

With respect to the socioeconomic variables of the households, there are also some differences between classes 1 and 2. Those subjects in class 1 are more likely than those in class 2 to prefer the less dense suburban and rural areas whenever they are of a lower level of income, higher age, not married and not native Spanish. The variable CHILDREN is not significant for class 2, but for class 1 it has a negative impact on the preference for suburban areas and a positive impact on the preference for rural areas. Thus, the differences between class 1 and 2 are noted not only in the higher parameter values found for class 2 but also in the signs and significance levels of the variables AGE, MARRIED, CHILDREN, and NATIVE.

The estimation of the class membership equations (Table 4) show that the probability to be included in class 2 is higher for those households with higher income, younger and that live in condominiums. Table 5 presents the mean statistics of the variables for the characterization of two classes raised by the LC model across all residential locations. Subjects in class 1 show on average higher levels of noise exposure, air pollution and delinquency perception than subjects in class 2. In addition, class 1 is also characterized by a larger number of persons in the household, and a higher proportion living in individual houses. Houses in class 1 have also a larger number of rooms. In respect of the socioeconomic characteristics, those in class 1 have a lower level of average income and higher age, are less likely to be married and have a smaller proportion of houses with children. However, there is no significant difference in terms of the nationality of the head of the household.

6. Discussion and concluding remarks

The tendency to urbanization is involving changes in the quality of life of individuals across society derived from the transformations of

Table 4
Statistics of the latent class models.

Classes	LLF	Nparam	AIC	BIC
1	−14,169.22	22	28,382.45	28,575.08
2	−14,015.03	45	28,226.03	28,463.04
3	−13,925.12	68	28,300,03	28,665.29
4	−13,892.83	91	28,331.04	28,715.43
5	−13,810.51	114	28,371,25	28,791.52

Table 5
Characteristics of households according to membership class.

Variable	Mean		S.D.	
	Class 1	Class 2	Class 1	Class 2
NOISE	0.17	0.12	0.29	0.32
AIR POLLUTION	0.09	0.06	0.21	0.17
DELINQUENCY	0.11	0.07	0.29	0.18
CONDOMINIUM	0.60	0.73	0.48	0.44
NUMBER OF ROOMS	0.68	0.57	0.46	0.49
HOUSEHOLD SIZE	0.77	0.75	0.41	0.43
INCOME	0.44	0.56	0.38	0.49
AGE	59.68	56.67	16.09	14.86
CHILDREN	0.31	0.36	0.46	0.48
MARRIED	0.17	0.21	0.37	0.41
NATIVE	0.90	0.91	0.29	0.27
N of observations	5410	10,226	5410	10,226

nature and social impacts (Legras and Cavailhes, 2016). For instance, natural assets such as landscapes, air quality and tranquillity can be altered because of the implementation of infrastructures related to urbanizations and their interconnections. In addition, there can emerge significant social impacts derived from urban segregation and sprawling (Dura-Guimera, 2003; Irwin and Bockstael, 2007; Chen et al., 2018).

Noise and air pollution are two of the most important environmental impacts of urbanization affecting citizens' health and quality of life (Schaeffer et al., 2016). Air pollution stands out as the first environmental stressor on human health and the quality of life while noise becomes second in Europe on this ranking (Stansfeld, 2015). Furthermore, there are social inequalities that have been demonstrated to be spatially linked to the impacts of air pollution and noise, with those living in less quality residential housing and income segregated areas being the most affected (European Commission, 2016; Verbeek, 2019).

There are many hedonic pricing studies proving that both air pollution and noise have impacts on the prices of residential housing, but only a few studies consider both impacts in the same model (Le Boennec and Salladarré, 2017). Furthermore, there is no evidence on the joint incidence of air pollution and noise on the residential choice between rural and urban areas. The present paper contributes to fill this research gap by looking at evidence from a large representative sample of households of the Spanish population. The data is modelled utilizing a random utility latent class approach that allows for the consideration of heterogeneous groups of individuals holding different preferences for the attributes determining residential choice (Lee et al., 2019).

The results show that the latent class model has a better performance than the mixed logit model for modelling the residential choice according to urban, suburban and rural areas. The model proves that the perceptions of noise and air pollution are significant variables in explaining the alternative residential choices of rural and suburban areas. These areas are characterized by a lower population density, and are preferred by those individuals that have lower perceptions of noise and air pollution than individuals in urban areas. The lower the perception of these environmental nuisances the higher is the likelihood of households living in less densely populated areas as those characterized by rural and some suburban environments.

In addition, the choices of rural and suburban residential areas are significantly explained by the role of socioeconomic and dwelling characteristics, as found in other studies of residential choice (Bhat et al., 2013; Ardeshiri and Vij, 2019; Blumenberg et al., 2019). Rural and suburban housing is more likely to be chosen by individuals with lower income, lower age, married and with Spanish nationality. Regarding the type of housing, condominiums are less likely to be preferred in rural areas where houses have a higher probability to be single units and of larger sizes.

The exploration of finite sample heterogeneity with the latent class model leads to the conclusion that the preferences for the rural and suburban zones in comparison to the urban alternative are not homogeneous across the population, since there are two classes of households with different preferences for the housing and environmental attributes that are spatially mixed in the territory. The first class corresponds to households that are based on rural and suburban zones because of their lower levels of noise and air pollution. However, the second class is formed by households that are willing to accept higher levels of noise for lower levels air pollution in the rural and suburban areas. This trade-off may be explained because of the fact that many urban and suburban areas can be affected by perceptible levels of noise from road traffic or from disturbing economic activities linked industry or agriculture, even though they still enjoy high levels of air quality.

Thus, the characterization of the alternative classes of households according to their preferences for rural and suburban zones suggest that spatial planning of rural and suburban areas have important challenges emerging from the spread of urbanization across the territory and the abandonment of agriculture (Siciliano, 2012; van der Zanden et al., 2017). Special attention should be paid to the heterogeneity in social preferences emerging from the different configurations of the environmental, social and housing attributes of the alternatives offered in the rural and urban zones with respect to the urban environments.

In general terms, empirical evidence is clear in the fact rural and suburban areas offer higher environmental quality because of the lower levels of noise and air pollution (Qin and Liao, 2016). However, the pressures coming from socioeconomic development and the influence of urban sprawling may be causing changes in these advantages (Tong and Kang, 2020; Schwela, 2021). This results in heterogeneity in the choice of residential location, thereby motivating households to adjust according to their preferences and socioeconomic conditions. Therefore, there can be found some areas in rural and suburban environments subject to relevant external effects that should be monitored and corrected through appropriate planning and policy perspectives (Valeri et al., 2016).

The results obtained in this research have some limitations raising questions that may be useful for guiding future efforts to assess the impacts of noise and air pollution in the rural and urban contexts. First, the variables indicating the affection of noise or air pollution in the household are based on perception measures that may not be correlated with the actual measurements of these impacts. Although some studies have indicated that subjective measures of noise and air pollution can be fair approximations of their objective counterparts, it may be more accurate to realize inference based on a combined measurement of subjective and objective assessments (Chiarini et al., 2020). Second, the data is based on actual residential choice by householders, and not on moving intentions or past moving history. However, some studies have suggested that the actual residential location closely reflects the preferred choice by householders, and that it has been determined by past moving decisions (Ströbele and Hunziker, 2017). An advantage of using current choices of household location is that they support a revealed preference approach based on observed real choices, and are not based on hypothetical questions about expectations that may fail to be realized. And finally, the results are based on a cross section of data at a point of time, which obviates the dynamic effects that may be occurring as a result of the rural and suburban transformations caused by urbanization and economic development.

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

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References

Ardeshiri, A., Vij, A., 2019. Lifestyles, residential location, and transport mode use: a hierarchical latent class choice model. Transp. Res. A Policy Pract. 126, 342–359.
Banzhaf, H.S., Walsh, R.P., 2008. Do people vote with their feet? An empirical test of Tiebout. Am. Econ. Rev. 98 (3), 843–863.
Barbero-Sierra, C., Marques, M.J., Ruíz-Pérez, M., 2013. The case of urban sprawl in Spain as an active and irreversible driving force for desertification. J. Arid Environ. 90, 95–102.
Bayer, P., Keohane, N., Timmins, C., 2009. Migration and hedonic valuation: the case of air quality. J. Environ. Econ. Manag. 58 (1), 1–14.
Bayoh, I., Irwin, E.G., Haab, T., 2006. Determinants of residential location choice: How important are local public goods in attracting homeowners to central city locations? J. Reg. Sci. 46 (1), 97–120.
Beilin, R., Lindborg, R., Stenseke, M., Pereira, H.M., Llausàs, A., Slätmo, E., Munro, N., 2014. Analysing how drivers of agricultural land abandonment affect biodiversity

and cultural landscapes using case studies from Scandinavia, Iberia and Oceania. Land Use Policy 36, 60–72.

Bhat, C.R., Guo, J.Y., 2007. A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels. Transp. Res. B Methodol. 41 (5), 506–526.

Bhat, C.R., Paleti, R., Pendyala, R.M., Lorenzini, K., Konduri, K.C., 2013. Accommodating immigration status and self-selection effects in a joint model of household auto ownership and residential location choice. Transp. Res. Rec. 2382 (1), 142–150.

Blanco, J.C., Flindell, I., 2011. Property prices in urban areas affected by road traffic noise. Appl. Acoust. 72 (4), 133–141.

Blumenberg, E., Brown, A., Ralph, K., Taylor, B.D., Turley Voulgaris, C., 2019. A resurgence in urban living? Trends in residential location patterns of young and older adults since 2000. Urban Geogr. 40 (9), 1375–1397.

Cardesin Diaz, J.M., Araujo, J.M., 2017. Historic urbanization process in Spain (1746–2013) from the fall of the American empire to the real estate bubble. J. Urban Hist. 43 (1), 33–52.

Carey, I.M., Anderson, H.R., Atkinson, R.W., Beevers, S.D., Cook, D.G., Strachan, D.P., Kelly, F.J., 2018. Are noise and air pollution related to the incidence of dementia? A cohort study in London, England. BMJ Open 8 (9), e022404.

Casey, J.A., Morello-Frosch, R., Mennitt, D.J., Fristrup, K., Ogburn, E.L., James, P., 2017. Race/ethnicity, socioeconomic status, residential segregation, and spatial variation in noise exposure in the contiguous United States. Environ. Health Perspect. 125 (7), 077017.

Chang, J.S., Kim, D.J., 2013. Hedonic estimates of rail noise in Seoul. Transp. Res. Part D: Transp. Environ. 19, 1–4.

Chasco, C., Gallo, J.L., 2013. The impact of objective and subjective measures of air quality and noise on house prices: a multilevel approach for downtown M adrid. Econ. Geogr. 89 (2), 127–148.

Chen, B., Liu, D., Lu, M., 2018. City size, migration and urban inequality in China. China Econ. Rev. 51, 42–58.

Chiarazzo, V., Coppola, P., Ibeas Portilla, Á., Ottomanelli, M., 2014. The effects of environmental quality on residential choice location. Procedia Soc. Behav. Sci. 162, 178–187.

Chiarini, B., D'Agostino, A., Marzano, E., Regoli, A., 2020. The perception of air pollution and noise in urban environments: a subjective indicator across European countries. J. Environ. Manag. 110272.

Cordera, R., Chiarazzo, V., Ottomanelli, M., dell'Olio, L., Ibeas, A., 2019. The impact of undesirable externalities on residential property values: spatial regressive models and an empirical study. Transp. Policy 80, 177–187.

de Andrés, M., Barragán, J.M., Sanabria, J.G., 2017. Relationships between coastal urbanization and ecosystems in Spain. Cities 68, 8–17.

Duncombe, W., Robbins, M., Wolf, D.A., 2001. Retire to where? A discrete choice model of residential location. Int. J. Popul. Geogr. 7 (4), 281–293.

Dura-Guimera, A., 2003. Population deconcentration and social restructuring in Barcelona, a European Mediterranean city. Cities 20, 387–394.

European Commission, 2016. Links between Noise and Air Pollution and Socioeconomic Status, Brussels.

European Commission, 2020. Methodological Guidelines and Description of EU-SILC Target Variables 2019 Operation. Eurostat, DocSILC065. https://circabc.europa.eu/sd/a/b862932f-2209-450f-a76d-9cfe842936b4/DOCSILC065%20operation%202019_V9.pdf.

Feijten, P., Hooimeijer, P., Mulder, C.H., 2008. Residential experience and residential environment choice over the life-course. Urban Stud. 45 (1), 141–162.

Flambard, V., 2017. Demand for housing choices in the north of France: a discrete approach. J. Eur. Real Estate Res 10 (3), 346–365.

Freeman, R., Liang, W., Song, R., Timmins, C., 2019. Willingness to pay for clean air in China. J. Environ. Econ. Manag. 94, 188–216.

Galster, G., Andersson, R., Mustered, S., 2010. Who is affected by neighbourhoood income mix?. Gender, age, family, employment and income differences. Urban Stud. 47 (1), 167–168.

García, J.A.B., Hernández, J.E.R., 2008. Housing demand in Spain according to dwelling type: microeconometric evidence. Reg. Sci. Urban Econ. 38 (4), 363–377.

García, J., Raya, J.M., 2011. Price and income elasticities of demand for housing characteristics in the city of Barcelona. Reg. Stud. 45 (5), 597–608.

Gómez-Antonio, M., Hortas-Rico, M., Li, L., 2016. The causes of urban sprawl in Spanish urban areas: a spatial approach. Spat. Econ. Anal. 11 (2), 219–247.

González, L., Ortega, F., 2013. Immigration and housing booms: evidence from Spain. J. Reg. Sci. 53 (1), 37–59.

Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis: contrasts with mixed logit. Transp. Res. B Methodol. 37 (8), 681–698.

Grout, C., Cavailhès, J., Détang-Dessendre, C., Thomas, A., 2016. Is sprawling residential behavior influenced by climate? Land Econ. 92 (2), 203–219.

Guo, J.Y., Bhat, C.R., 2007. Operationalizing the concept of neighborhood: Application to residential location choice analysis. J. Transp. Geograph. 15 (1), 31–45.

Hankey, S., Marshall, J.D., 2017. Urban form, air pollution, and health. Curr. Environ. Health Rep. 4 (4), 491–503.

Hess, S., Ben-Akiva, M., Gopinath, D., Walker, J., 2008. Advantages of latent class models over continuous mixture models in capturing heterogeneity. In: In European Transport Conference, Proceeding.

Ibraimovic, T., Hess, S., 2018. A latent class model of residential choice behaviour and ethnic segregation preferences. Hous. Stud. 33 (4), 544–564.

Irwin, E.G., Bockstael, N.E., 2007. The evolution of urban sprawl: evidence of spatial heterogeneity and increasing land fragmentation. Proc. Natl. Acad. Sci. 104 (52), 20672–20677.

Jariwala, H.J., Syed, H.S., Pandya, M.J., Gajera, Y.M., 2017. Noise pollution & human health: a review. Indoor Built. Environ. 1–4.

Kim, J.H., Pagliara, F., Preston, J., 2005. The intention to move and residential location choice behaviour. Urban Stud. 42 (9), 1621–1636.

King, K.E., 2015. Chicago residents' perceptions of air quality: objective pollution, the built environment, and neighborhood stigma theory. Popul. Environ. 37 (1), 1–21.

Le Boennec, R., Salladarré, F., 2017. The impact of air pollution and noise on the real estate market. The case of the 2013 European green capital: Nantes, France. Ecol. Econ. 138, 82–89.

Le Gallo, J., Chasco, C., 2008. Spatial analysis of urban growth in Spain, 1900–2001. Empir. Econ. 34 (1), 59–80.

Lee, H., 2020. Are millennials coming to town? Residential location choice of young adults. Urban Aff. Rev. 56 (2), 565–604.

Lee, Y., Circella, G., Mokhtarian, P.L., Guhathakurta, S., 2019. Heterogeneous residential preferences among millennials and members of generation X in California: a latent-class approach. Transp. Res. Part D: Transp. Environ. 76, 289–304.

Legras, S., Cavailhes, J., 2016. Environmental performance of the urban form. Reg. Sci. Urban Econ. 59, 1–11.

Liao, F.H., Farber, S., Ewing, R., 2015. Compact development and preference heterogeneity in residential location choice behaviour: a latent class analysis. Urban Stud. 52 (2), 314–337.

Loschiavo, D., 2019. Big-City Life (Dis) Satisfaction? The Effect of Living in Urban Areas on Subjective Well-Being (No. 1221). Bank of Italy, Economic Research and International Relations Area.

Lotfi, S., Despres, C., Lord, S., 2019. Are sustainable residential choice also desirable? A study of household satisfaction and aspirations with regard to current and future residential location. J. Housing Built Environ. 34 (1), 283–311.

Lu, J., 2020. Household residential location choice in retirement: the role of climate amenities. Reg. Sci. Urban Econ. 103489.

Ma, W., Jiang, G., Li, W., Zhou, T., 2018. How do population decline, urban sprawl and industrial transformation impact land use change in rural residential areas? A comparative regional analysis at the peri-urban interface. J. Clean. Prod. 205, 76–85.

Manisalidis, I., Stavropoulou, E., Stavropoulos, A., Bezirtzoglou, E., 2020. Environmental and health impacts of air pollution: a review. Front. Public Health 8, 14.

Mariel, P., Hoyos, D., Meyerhoff, J., Czajkowski, M., Dekker, T., Glenk, K., Thiene, M., 2021. Environmental Valuation with Discrete Choice Experiments: Guidance on Design, Implementation and Data Analysis. Springer Nature.

Marois, G., Lord, S., Negron-Poblete, P., 2018. The residential mobility of seniors among different residential forms: analysis of metropolitan and rural issues for six contrasted regions in Québec, Canada. J. Hous. Elder. 32 (1), 73–98.

Marois, G., Lord, S., Morency, C., 2019. A mixed logit model analysis of residential choices of the young-elderly in the Montreal metropolitan area. J. Hous. Econ. 44, 141–149.

McFadden, D., 1978. Modelling the choice of residential location. In: Karlqvist, A., Lundqvist, L., Snickars, F., Weibull, J. (Eds.), Spatial Interaction Theory and Planning Models. North Holland, Amsterdam, pp. 75–96.

McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. J. Appl. Econ. 15 (5), 447–470.

McGranahan, D.A., Wojan, T.R., Lambert, D.M., 2011. The rural growth trifecta: outdoor amenities, creative class and entrepreneurial context. J. Econ. Geograph. 11 (3), 529–557.

Meen, G., 2016. Spatial housing economics: a survey. Urban Stud. 53 (10), 1987–2003.

Munroe, D.K., 2007. Exploring the determinants of spatial pattern in residential land markets: amenities and disamenities in Charlotte, NC, USA. Environ. Plan. B. 34 (2), 336–354.

Navarro, M., D'Agostino, A., Neri, L., 2020. The effect of urbanization on subjective well-being: explaining cross-regional differences. Socio Econ. Plan. Sci. 100824.

Nelson, J.P., 1982. Highway noise and property values: a survey of recent evidence. J. Transp. Econ. Policy 117–138.

Nickkar, A., Shin, H.S., Lee, Y.J., 2020. Willingness to pay for connected vehicles: an alternative-specific mixed logit regression approach. Int. J. Traffic Transp. Eng. 10 (2).

Olaru, D., Smith, B., Taplin, J.H., 2011. Residential location and transit-oriented development in a new rail corridor. Transp. Res. A Policy Pract. 45 (3), 219–237.

Paleti, R., Mishra, S., Haque, K., Golias, M.M., 2020. Latent class analysis of residential and work location choices. Transp. Lett. 1–11.

Park, J., Kim, K., 2016. The residential location choice of the elderly in Korea: a multilevel logit model. J. Rural. Stud. 44, 261–271.

Qin, H., Liao, T.F., 2016. The association between rural–urban migration flows and urban air quality in China. Reg. Environ. Chang. 16 (5), 1375–1387.

Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. J. Political Econ. 82 (1), 34–55.

Schaeffer, Y., Cremer-Schulte, D., Tartiu, C., Tivadar, M., 2016. Natural amenity-driven segregation: evidence from location choices in French metropolitan areas. Ecol. Econ. 130, 37–52.

Schirmer, P.M., van Eggermond, M.A., Axhausen, K.W., 2014. The role of location in residential location choice models: a review of literature. J. Transp. Land Use 7 (2), 3–21.

Schwela, D., 2021. Review of environmental noise policies and economics in 2014-2016. South Florida J. Health 2 (1), 46–61.

Siciliano, G., 2012. Urbanization strategies, rural development and land use changes in China: a multiple-level integrated assessment. Land Use Policy 29 (1), 165–178.

Smith, V.K., Huang, J.C., 1993. Hedonic models and air pollution: twenty-five years and counting. Environ. Resour. Econ. 3 (4), 381–394.

Smith, B., Olaru, D., 2013. Lifecycle stages and residential location choice in the presence of latent preference heterogeneity. Environ. Plan. A 45 (10), 2495–2514.

Stansfeld, S.A., 2015. Noise effects on health in the context of air pollution exposure. Int. J. Environ. Res. Public Health 12 (10), 12735–12760.

Ströbele, M., Hunziker, M., 2017. Are suburbs perceived as rural villages? Landscape-related residential preferences in Switzerland. Landsc. Urban Plan. 163, 67–79.
Szczepańska, A., Senetra, A., Wasilewicz-Pszczółkowska, M., 2015. The effect of road traffic noise on the prices of residential property–a case study of the polish city of Olsztyn. Transp. Res. Part D: Transp. Environ. 36, 167–177.
Tong, H., Kang, J., 2020. Relationship between Urban Development Patterns and Noise Complaints in England. Urban Analytics and City Science, Environment and Planning B, 2399808320930247.
Train, K.E., 2009. Discrete Choice Methods with Simulation. Cambridge university press.
Valeri, E., Gatta, V., Teobaldelli, D., Polidori, P., Barratt, B., Fuzzi, S., Maione, M., 2016. Modelling individual preferences for environmental policy drivers: empirical evidence of Italian lifestyle changes using a latent class approach. Environ. Sci. Pol. 65, 65–74.
van Dam, F., Heins, S., Elbersen, B.S., 2002. Lay discourses of the rural and stated and revealed preferences for rural living. Some evidence of the existence of a rural idyll in the Netherlands. J. Rural Studies 18 (4), 461–476.
van der Zanden, E.H., Verburg, P.H., Schulp, C.J., Verkerk, P.J., 2017. Trade-offs of European agricultural abandonment. Land Use Policy 62, 290–301.
Verbeek, T., 2018. The relation between objective and subjective exposure to traffic noise around two suburban highway viaducts in Ghent: lessons for urban environmental policy. Local Environ. 23 (4), 448–467.
Verbeek, T., 2019. Unequal residential exposure to air pollution and noise: a geospatial environmental justice analysis for Ghent, Belgium. SSM-Populat. Health 7, 100340.
Von Graevenitz, K., 2018. The amenity cost of road noise. J. Environ. Econ. Manag. 90, 1–22.
Von Szombathely, M., Albrecht, M., Augustin, J., Bechtel, B., Dwinger, I., Gaffron, P., Strüver, A., 2018. Relation between observed and perceived traffic noise and socio-economic status in urban blocks of different characteristics. Urban Sci. 2 (1), 20.
Walker, J.L., Li, J., 2007. Latent lifestyle preferences and household location decisions. J. Geogr. Syst. 9 (1), 77–101.
Zondag, B., Pieters, M., 2005. Influence of accessibility on residential location choice. Transp. Res. Record 1902 (1), 63–70.