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Valuing access to urban greenspace using non-linear distance decay in hedonic property pricing

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ABSTRACT

Modelling walking distance enables the observation of non-linearities in hedonic property pricing of accessibility to greenspace. We test a penalized spline spatial error model (PS-SEM), which has two distinctive features. First, the PS-SEM controls for the presence of a spatially autocorrelated error term. Second, the PS-SEM allows for continuous non-linear distance decay of the property price premium as a function of walking distance to greenspaces. As a result, compared with traditional spatial econometric methods, the PS-SEM has the advantage that data determines the functional form of the distance decay of the implicit price for greenspace accessibility. Our PS-SEM results from Oslo, Norway, suggest that the implicit price for greenspace access is highly non-linear in walking distance, with the functional form varying for different types of greenspaces. Our results caution against using simple linear distances and assumptions of log or stepwise buffer-based distance decay in property prices relative to pedestrian network distance to urban amenities. The observed heterogeneity in the implicit property prices for walking distance to greenspace also provides a general caution against using non-spatial hedonic pricing models when aggregating values of greenspace amenities for policy analysis or urban ecosystem accounting purposes.

1. Introduction

Walking accessibility to everyday destinations, such as schools, restaurants and greenspaces has been associated with better health (Creatore et al., 2016), lower crime rates, fewer foreclosures and increased property values (Gilderbloom et al., 2015). These associations taken together make promotion of pedestrian accessibility to urban amenities a fundamental strategy in urban planning (Anderson and West, 2006; Czembrowski and Kronenberg, 2016). Accessibility to recreation in greenspace is an important urban ecosystem service (Gómez-Baggethun and Barton, 2013) providing well-being and health and determining choice of and willingness to pay for residential location. Studies showing higher real estate prices due to accessibility to greenspace can provide urban planners with arguments to support for public funding for greenspaces, cost sharing with private urban developers, as well as providing developers with support for marketing greenspace accessibility to potential homeowners.

The hedonic pricing method (HPM) is the workhorse of housing price analysis to estimate implicit prices of property attributes (Kain and Quigley, 1970; Rosen, 1974). It allows estimation of revealed preferences by treating housing as a good composed of many different attributes that together determine the price. It uses multivariate regression analysis to estimate the individual effects of the property and neighbourhood attributes on real-estate prices to infer marginal willingness to pay for each attribute (Rosen, 1974). In the applications of HPM to housing markets, attributes usually include property structural attributes and neighbourhood amenities such as, in our study, greenspaces with different attributes.

Havinga et al. (2020) defined ‘amenity services’ from ecosystems as the information flow from the knowledge that a natural area such as a park or forest is visible, accessible and or unique to the location (p.6). The marginal willingness to pay for pedestrian accessibility to

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greenspace revealed in property prices has been shown to decline with distance across many different property market settings with few exceptions (Crompton and Nicholls, 2020; Crompton and Nicholls, 2021). The decline in willingness to pay for ecosystem services delivered at a distance from residential location – known as 'distance decay' – has also been observed in many stated preference valuation settings (e.g. Badura et al., 2020; Bateman et al., 2006; Johnston et al., 2019; Schaafsma et al., 2013; Soderberg and Barton, 2014; Yamaguchi and Shah, 2020). Distance decay may vary by direction (Schaafsma et al., 2012), be spatially discontinuous (Johnston and Ramachandran, 2014; Olsen et al., 2020) and is expected to be highly non-linear, particularly for pedestrian accessibility in urban settings (Millward et al., 2013; Moudon and Lee, 2009).

Non-linearity of distance decay may be due to spatial heterogeneity of greenspace attributes. Various proxy indicators for urban greenspace quality have been used in hedonic pricing. Czembrowski and Kronenberg (2016) found significant positive implicit prices for vegetation density, large parks, forest greenbelt, small forests, and negative implicit prices for cemeteries, using an ordinary least squares (OLS) model with linear prices and log-distances. Proximity to different greenspaces differentiated by function and size has been found to affect house prices both positively (Conway et al., 2010; Czembrowski and Kronenberg, 2016; Garrod and Willis, 1992a; Garrod and Willis, 1992b; Melichar and Kaprová, 2013; Poudyal et al., 2009; Tyrväinen and Miettinen, 2000) and sometimes negatively, depending on vegetation type or function (Czembrowski and Kronenberg, 2016; François et al., 2002). A number of studies have found mostly significant positive effects of greenspace attributes on property values, notably green cover and urban trees (Dombrow et al., 2000; Donovan and Butry, 2010; Escobedo et al., 2015; Holmes et al., 2006; Kadish and Netusil, 2012; Mansfield et al., 2005; Morales et al., 1983; Sander et al., 2010; Mei et al., 2018), but sometimes negative (Thompson et al., 1999; Saphores and Li, 2012).

Different hedonic pricing methods have been utilized in economic analyses of access to amenity services. Hedonic pricing of urban amenities often models the effect of property prices as a linear, log-linear or log–log distance decay function. While early hedonic models used Euclidean distance, GIS and model developments in the last couple of decades have enabled measurement of distances along street networks (Crompton and Nicholls, 2020). Network distance measurements such as walking distance are more suitable than Euclidean distances in spatial analysis of accessibility (Lu et al., 2011, 2014; Shen and Karimi, 2017). Computing non-linear walking distance to greenspace as street network distance is increasingly common (Czembrowski and Kronenberg, 2016; Nicholls and Crompton, 2005; Tyrväinen, 1997; Lu, Charlton and Fotheringham, 2011; Lu et al., 2014; Shen and Karimi, 2017). More advanced approaches have recently been used for deeper exploration of the impact of walking distance to greenspace on real estate markets. For example, Sylla et al. (2019) and Kopczewska and Ćwiakowski (2021) applied geographically weighted regression models to explore spatially heterogeneous impacts of protected areas, forests, rivers, trees, and landscape diversity on real estate markets. Although there are some examples of hedonic pricing models that have estimated distance decay functions for access to greenspace (e.g. Daams et al., 2016; Graevenitz and Panduro, 2015; Łaszkiewicz et al., 2019), none of them has focused on exploring the nature of non-linear distance decay functions for greenspace.

If economic valuation of amenities from greenspace is to inform urban planning and ecosystem accounting, it requires modelling that is sensitive to spatial variation in the heterogeneous urban fabric (Gómez-Baggethun and Barton, 2013). The present paper contributes to the urban ecosystem service valuation literature by demonstrating a flexible econometric model that can address the non-linear relationship between residential prices and pedestrian network walking distance. Instead of using predefined functions for distance decay, such as log-linear or linear, which may oversimplify the relationship between walking distance and real estate prices (Łaszkiewicz et al., 2019), we recover the rich structure of the value function for walking distance by allowing for non-linearity using a penalized spline spatial error model (PS-SEM).

The paper has the following structure. In Section 2, we describe our case study city – Oslo – and the data. In Section 3, we provide the description of the methods, starting from a brief introduction of hedonic price model (3.1), through econometric models (3.2–3.4), the quantification of walking accessibility variables (3.5), ending up with the specification of other variables (3.6). Section 4 contains the empirical results and Section 5 discusses them. We end with some concluding remarks.

2. Case study site

Our study was carried out in Oslo, Norway's capital city and largest city, with an official population of 693 000 in 2020, predicted to grow to about 801 000 by 2050 (Leknes and Løkken, 2020). Until recently one of the fastest growing population of European capitals has caused a housing shortage and steady housing price increases. Oslo municipality has a vision for a more walkable city (Tjernshaugen, 2015). This includes reducing car accessibility in favour of walking and biking access, first and foremost in the city centre. The housing market in Oslo consists mainly of owner occupiers, both in apartments and detached houses. There is also a segment of housing cooperatives and a relatively small rental market, where many of the rented apartments are privately owned and sublet on a free market.

In the only prior hedonic pricing study of greenspace in Oslo, Traaholt (2014) tested linear regression model estimated using ordinary last square method (OLS), spatial econometric models and a generalized additive model (GAM) for regulated greenspaces (parks, playgrounds, sports arenas, cemeteries and peri-urban forest (in Norwegian language: *Marka*)) (Fig. 1). Models used continuous linear Euclidean distance accessibility measures to regulated greenspaces. Extensive manual testing was conducted to find specific maximum distance thresholds for each type of greenspace. Only the OLS models observed significant effects of linear Euclidean distance measures on the logarithm of property prices across all regulated greenspace types. In a pilot study of economic values of greenspace Barton et al. (2015) used Traaholt (2014) OLS model to calculate an aggregate contribution of greenspaces in Oslo to property value, across all apartments in the city. Recognizing the limitations of the simple OLS model for scaling values for urban ecosystem accounting, Barton et al. (2015) called for further exploration of robust models that control for spatial effects. The present paper follows up robustness checks on hedonic valuation of greenspace in Oslo, using a PS-SEM with general relevance also beyond the Oslo case study. We also take advantage of data on non-environmental neighbourhood amenities and services not available in the Traaholt (2014) study.

3. Materials and methods

3.1. Data

Different sub-markets of the housing market should be estimated using different models (Palmquist, 2005). This study investigates owner occupied apartments only, as we consider it a separate market from housing cooperatives and single-family houses. Consequently, conclusions cannot be drawn from our results for preferences in other markets. The sales data was provided by Ambita AS[1] at the resolution of address points, and originally based on two data sets combined: firstly, the sales prices from the Tax Agency (Skatteetaten) and secondly, structural attributes for all apartments in Land Survey Registers (Kartverket). The set consisted of all registered sales between 2007 and 2015.

We cleaned the data using some simple exclusion criteria. We only

[1] A private company that provides official data on property transactions and characteristics in Norway.

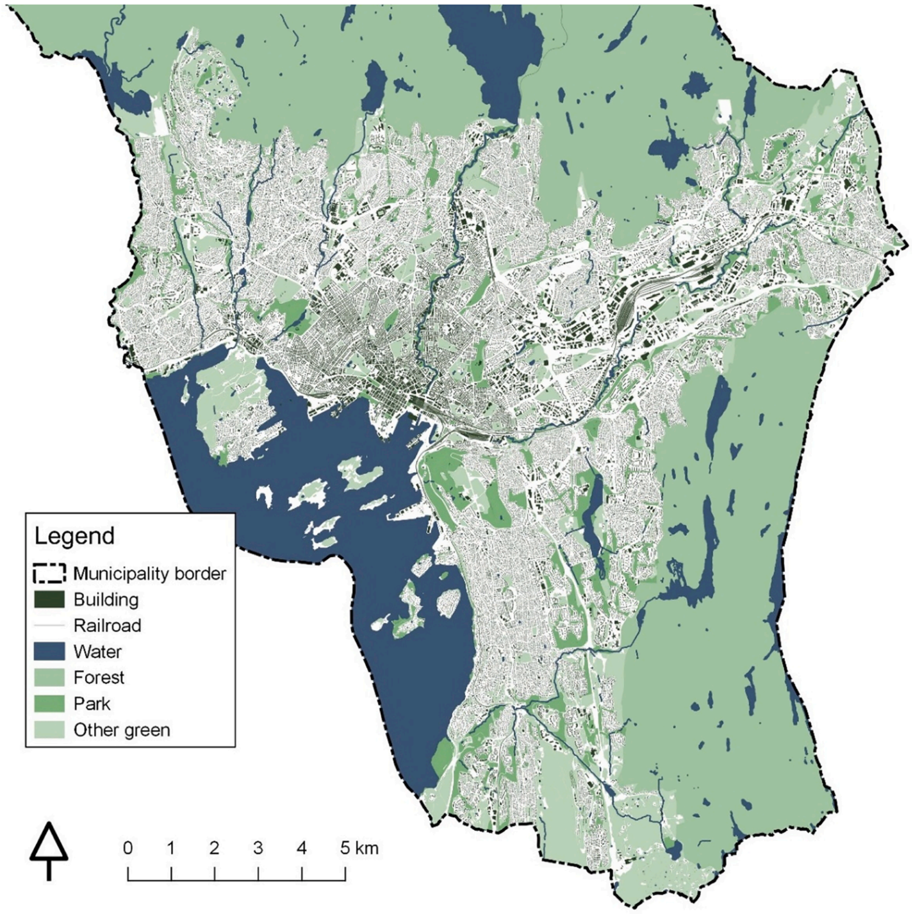

Fig. 1. Overview map over the urban part of Oslo municipality, showing the great natural reserves north and east of the city and the fjord in the southwest.

used observations that were registered as sales on a free market, had coordinates attached to them, were registered as a dwelling and were larger than 10 m^2. We used a house price index for apartments in Oslo, provided by Statistics Norway, to calculate real (in 2nd quarter 2015 prices) per square meter apartment prices. As a final step, we omitted observations in the highest and lowest percentile of price per square meter, as well as other outliers, to get a sample without the extreme values that can be considered a sub-market, ending up with $N = 41{,}805$ observations. We used price per square meter rather than total sale price, to standardize the prices as they to a large extent are determined by housing size (Tyrväinen, 1997). Using the price per square metre as a dependent variable enabled analysis of the additional effect of proximity to different amenities on prices, which are more clearly expressed in relative prices than absolute prices (Liebelt et al., 2018).

We had access to data for the 2007–2015 period. Our analysis period is long enough to include short term market shocks, but not long enough to see significant changes in land use. Within this time period, the global financial crisis occurred, but the Oslo housing market only experienced a small downturn, mainly because of the guarantee for mortgages by the Norwegian government (Røed Larsen, 2018). We did not have access to longitudinal data for the individual property. All of our hedonic pricing models used time fixed effects for quarters and years to control for temporal fluctuations in real estate prices.

To quantify urban form, we used geographical data on a variety of network infrastructure and amenities in the city. We obtained most of the data at non-aggregated level, e.g., businesses at address point level, and water and greenspaces as polygons. Due to privacy, the socioeconomic data was obtained at aggregate level of city district and census tracts.

In Table 1, the data sources are listed for all variables included in the analysis. The initial list of variables contained 62 potential covariates, including distance to the central business district, tram stops, commuter train stations, bars, restaurants, and many others that are not described in this paper. Greenspace amenity services were proxied using walking distances to different greenspace sizes, specific peri-urban forests and coastline. We reduced the initial list based on the results from previous hedonic pricing models and based on the result of the stepwise regression. The set of neighbourhood explanatory variables with data sources is presented in Table 1.

3.2. Accessibility related attributes

All walking distances to amenities were measured with the PST plugin for QGIS software (QGIS Development Team, 2009; Ståhle et al., 2005), and their specifications are given below. We used an axial map, a representation of space, as the network to measure walking distance. The axial map has its origins in space syntax research and consists of a network of the longest and fewest axial lines (Hillier and Hanson, 1989). We measured walking distance to attractions and amenities that have consistently predicted residential prices in the hedonic pricing literature, including proximity to schools, public transport, water bodies, greenspace and commercial and cultural amenities (Dieleman, Dijst, and Burghouwt, 2002; Iacono et al., 2008; Millward et al., 2013; Moudon and Lee, 2009; Yang and Diez-Roux, 2012). All street segments except motorways are pedestrian, and the calculated network distances capture the pedestrian areas of the city. Distance to highways was measured to the nearest highway exit.

Accessibility to school can be measured in different ways: school quality as measured by average scores or points, e.g. SAT score or average grades (Li et al., 2015), distance to closest school (Dai et al.,

Table 1
Description of neighbourhood variables, including walking accessibility and amenity variables.

Variable name	Variable description	Previous studies with similar specification	Data source
Distance to pocket park	Network distance to a park smaller than 1000 m^2	Czembrowski and Kronenberg (2016); Kommune (2009)	The Agency for Urban Environment (BYM) in Oslo Municipality
Distance to small park	Network distance to a park between 1000 and 5000 m^2		
Distance to medium park	Network distance to a park between 5000 and 100 000 m^2		
Distance to large park	Network distance to a park larger than 100 000 m^2		
Distance to Marka N	Walking distance to the nature area surrounding the city of Oslo in the north	Heyman et al. (2017); Sjaastad et al. (2008)	The Agency for Urban Environment (BYM) in Oslo Municipality
Distance to Marka E	Walking distance to the nature area surrounding the city of Oslo in the east		
Socioeconomic index	Average employment, education and income level on census tract (grunnkrets). The income is disaggregated from the level of city district (bydel).	Li et al. (2015); Zabel (2015)	Statistics Norway (Statistisk Sentralbyrå)
Distance to commercial amenities	Shortest network distance to reach restaurant, bar and shop	Chasco and Le Gallo (2015); Jang and Kang (2015); Wen, Zhang, and Zhang (2014)	Statistics Norway & The Oslo School of Architecture and Design
Distance to cultural amenities	Shortest network distance to reach art gallery, cinema, museum and library	Rich and Nielsen (2004); Thériault et al. (2005)	Statistics Norway & The Oslo School of Architecture and Design
Distance to school	Network distance to closest primary school	Dziauddin, Alvanides, and Powe, (2013)	Statistics Norway & The Oslo School of Architecture and Design
Distance to fjord	Network distance to the fjord (coastline)	Abelson, Joyeux, and Mahuteau, (2013); Yoo et al. (2014)	The Agency for Urban Environment (BYM) in Oslo Municipality
Distance to metro	Network distance to the closest metro station	Cervero and Kang (2011); Jayantha and Lam (2015)	The Agency for Urban Environment (BYM) in Oslo Municipality
Distance to highway	Network distance to the closest highway exit	Li et al. (2015); Mitra and Saphores (2016)	The Oslo School of Architecture and Design
Noise below 55	Dummy variable for modelled noise below 55 dB (reference category)	Baranzini, Schaerer, and Thalmann (2010)	The Agency for Urban Environment (BYM) in Oslo Municipality
Noise 55–64	Dummy variable for modelled noise from 55 to 64 dB		
Noise 65+	Dummy variable for modelled noise 65 dB and more		

2016) or number of schools within a distance or district (Chasco and Le Gallo, 2015). In this study we focused on the walking distance to primary schools.

Access to public transport has similar alternatives in measurement specification as accessibility to schools. One can measure the number of stations or stops within a distance or district (Dai et al., 2016), distance to the closest station or stop (Cervero and Kang, 2011; Duncan, 2011) or with a gravitational measure that weights the measure to the level of service of the station or stop in terms of trip frequencies (Martínez and Viegas, 2009). In our study, we used walking distance to stations for commuter rail, metro, and tram.

Water as recreation amenity was included as the walking distance to the closest body of water, including the sea and lakes. While most studies estimating access to water use minimum distance (see for example Wen et al., 2014), there are examples measuring the percentage of water surfaces within a radius (Kestens et al., 2004) or assessing whether the dwelling is located adjacent to water (Bowman et al., 2009).

Greenspace can be classified according to functional types (Ståhle, 2006), by attributes or by size. Greenspace size is related to diversity of park functional attributes (Massoni et al., 2018) and size has been shown to be a proxy for function (Czembrowski and Kronenberg, 2016). Greenspaces were therefore further categorized by size (pocket, small, medium, and large parks). The categorization of greenspace sizes was determined by the municipal regulation plan of Oslo. Oslo Municipality's 2010 Green Plan specifies standard walking distances from homes to city parks of different sizes for testing park accessibility of the population: 250 m for small parks (0.1–0.5 ha), 500 m for medium parks (0.5–10 ha), and 1000 m for large parks (>10 ha). Oslo's planning norm requires at least one small park within 250 m and one medium park within 500 m of residences in the inner city, and one medium park within 500 m of residences in the outer city.

The designation of greenspace is stable over the period of study, as opposed to vegetation landcover as determined by remote sensing. Our designated land use approach does not capture access to unregulated public areas and greenspace on private land such as gardens. The peri-urban forest called 'Marka'[2] was divided into two geographically separated natural reserves, the East and North Marka, which have distinct natural attributes.

Urban design studies suggest that the access to multiple amenities is a key feature of neighbourhood quality (Lundhede et al., 2013). We specified two composite variables for amenities not related to greenspace, one for 'cultural amenities' (art galleries, museums, cinemas, and libraries) and one for 'commercial amenities' (bars, restaurants, and shops). Both measure the walking distance to reach all types of amenities in the respective category.

3.3. Other attributes not using accessibility metrics

Our sample consisted of apartment sales with structural attributes of the individual apartments, obtained from Ambita AS. In our analysis, we included the following structural attributes: size (in m^2), presence of elevator, number of bathrooms, number of floor levels from the top floor, number of rooms, year of obtaining permit for construction or major renovation (as a set of dummies 'last renovation' for three periods: before 2000, 2000–2009, after 2009) and the annual quarter the property was sold.

Noise was included using a GIS polygon layer for three different levels of noise: below 55 dB (reference category), from 55 to 64 dB and 65 dB or more. The noise levels were interpolated from measuring points for traffic intensities and do not take building height or vegetation into

[2] Literally translated, *Marka* means the outfield, the woodland, or the forest in Norwegian. In places like Oslo, *Marka* means urban forest, which is a large area of undeveloped land that is covered in vegetation and accessible to the general public. A *Marka* is therefore similar to a greenbelt in other countries.

consideration (Kommune, 2013). We did not include separate air pollution variables as this is mainly generated by traffic, and highly correlated with noise levels.

We specified a neighbourhood socioeconomic index from the level of employment, education, and income. The index was set as the average value (between 0 and 100) from the three components, specified as follows.

$$s_{ij} = \frac{\left(\frac{em_j - \min_j\{em_j\}}{\max_j\{em_j\} - \min_j\{em_j\}} + \frac{ed_j - \min_j\{ed_j\}}{\max_j\{ed_j\} - \min_j\{ed_j\}} + \frac{i_j - \min_j\{i_j\}}{\max_j\{i_j\} - \min_j\{i_j\}}\right)}{3} \cdot 100,$$

where s_i is socioeconomic index for *i*th apartment located in *j*th census tract; em_i is employment level for *j*th census tract; ed_i is education level for *j*th census tract and i_i is income for *j*th census tract.

The data for employment and education were available at census tract level of which there are $j = 540$ in the research area. Income was obtained on the more aggregate level of 16 city districts. To make use of all three variables, we assigned uniform district income levels to census tract level within the same district. Income was measured as average yearly income and standardized. For employment levels, we divided the number of employed with the total number of employable persons within each census tract to get a standardized value. In the same fashion, we calculated the share of people with a degree from college or university education longer than three years within the age of 20 to 64.

3.4. Modelling approaches

We estimated the hedonic price model as a penalized spline spatial error model (PS-SEM) to allow for a flexible non-linear relationship between housing prices and walking distance to various destinations, and judge whether it coincides with walking distance. Also, we supplement the results obtained using the PS-SEM with other econometrics models (provided in ESM Section 2) to show the robustness/sensitivity of the PS-SEM results and highlight which of our results need to be interpreted with caution.

Similar to other studies (Basile et al., 2014; Montero et al., 2018), we chose PS-SEM for two reasons: (1) to capture potential non-linear impact of covariates on the apartment prices (distance decay function) and (2) to control for the spatially correlated property prices. Below we provide further arguments for choosing PS-SEM as an appropriate method to deal with non-linearity in distance decay functions, which simultaneously controls for spatial autocorrelation.

3.4.1. Distance decay functions

The hedonic price models often assume a linear impact of covariates on home prices or use a predefined functional form to approximate the non-linear relationship in a parametric approach. However, willingness to walk is expected to be non-linear in a network with varied spatial configuration, with additional variation caused by residents' age, seasonal conditions and type of destination (Koushki Parviz Amir, 1988; Moudon and Lee, 2009; Yang and Diez-Roux, 2012). Therefore, a flexible distance decay functional form is important. In this study, we used PS-SEM, which uses a semi-parametric approach – the same as in a generalized additive model (GAM) (Wood, 2017) – to estimate the non-linear distance decay function. We chose the PS-SEM because it enabled capturing non-linearity of distance decay in a more flexible way than linear or log-linear models (Anderson and West, 2006; Kong et al., 2007). In particular, the PS-SEM uses penalized splines that enable estimating the fluctuations in the relationship between explanatory and outcome variables. This allowed us to go beyond the simple conclusions about positive/negative/no association between walking distance and property prices that is common to the linear or log-transformation of the covariates (Bao and Wan, 2004). The semi-parametric distance decay function is expected to more readily fit the local neighbourhood variation in perception of accessibility to different types of amenities (Iacono et al., 2008; Yang and Diez-Roux, 2012).

To demonstrate the usefulness of PS-SEM distance decay functions, we compared them with the simplest solutions such as (1) natural logarithm of distance to amenities, (2) stepwise distance decay function specified using an interaction between the natural logarithm of distance and a set of dummies for distance thresholds and (3) the greenspace coverage in the circular buffers <100 m, 100–250 m, 250–500 m, 500–1000 m, >1000 m (Crompton and Nicholls, 2021) (ESM Section 3).

3.4.2. Spatial autocorrelation

In the hedonic pricing models spatially correlated property prices are often observed. It occurs due to the inability of a model to control for all important locational attributes such as proximity externalities or neighbourhood features, leading to spatially-correlated omitted variables (Czembrowski and Kronenberg, 2016). To deal with spatially correlated property prices it is necessary to extend the non-spatial hedonic price model. Spatial econometric models use spatially lagged dependent and/or independent variables and/or spatially lagged error term to address this (Czembrowski and Kronenberg, 2016; Kim et al., 2018; Votsis, 2017). Other approaches include adding spatial fixed effects (Anselin and Arribas-Bel, 2013) or a smoothing function of geographical coordinates (spatial geo-additive gradient) (Łaszkiewicz et al., 2019; Veie et al., 2013). However, as was pointed out by Anselin and Arribas-Bel (2013), the former rarely removes spatial autocorrelation, while the latter might be more useful if spatial drift instead of autocorrelation occurs (Dormann et al., 2007).

Considering the above, we chose PS-SEM because it enabled us to control for spatial autocorrelation using a well-established spatial econometrics approach (Anselin et al., 2013). In particular, we captured spatial autocorrelation by enabling the error term in the PS-SEM to be spatially correlated. This approach requires *a priori* specification of a spatial weight matrix so it could be seen as less flexible than a data-driven spatial geo-additive gradient commonly used in the GAM (Valtiala et al., 2019). Nevertheless, the PS-SEM allows to capture spatial autocorrelation arising from spatially-correlated omitted variables (Basile et al., 2014; Montero et al., 2018).

To assess whether the PS-SEM should be preferred over other econometric models, we conducted an extensive evaluation of spatial autocorrelation using several alternative modelling techniques (see ESM Section 2 for details).

3.5. A penalized spline spatial error model

We estimated PS-SEM (Basile et al., 2014; Montero et al., 2018), specified as follows:

$$\begin{aligned} ln y_i &= \beta_0 + \beta_1 z_{1i} + \dots + \beta_k z_{ki} + f_1(x_{1i}) + \dots + f_l(x_{li}) + u_i \\ u_i &= \lambda \sum_{j=1}^{n} w_{ij} u_j + \varepsilon_i, \end{aligned} \tag{1}$$

where y_i is sales price per square meter for *i*th apartment; $z_{1i},\dots, z_{ki}$ are the explanatory variables representing structural attributes, time and spatial fixed effects. Impact of $z_{1i},\dots, z_{ki}$ on the outcome variable is assumed to be linear. $x_{1i},\dots, x_{li}$ are the explanatory variables representing property structural and neighbourhood attributes, such as the walking distance variables. Impact of $x_{1i},\dots, x_{li}$ on the outcome variable is assumed to be unknown and non-linear. $\beta_0,\dots, \beta_k$ are estimated parameters; $f_1,\dots, f_l$ are nonparametric smoothing functions representing distance decay; λ is a spatial autoregressive parameter; w_{ij} is an element of the spatial weight matrix $\mathbf{W}$; μ_i is spatially autocorrelated disturbance and ε_i follows a normal distribution, i.e., $\varepsilon \sim N(0,\sigma_\varepsilon^2)$.

The histogram of the outcome variable and descriptive statistics for explanatory variables are provided in Electronic Supplementary Materials (ESM Fig. 1 and ESM Table 1, respectively).

As stated, in PS-SEM we do not need *a priori* knowledge about the functional form of the relationship between explanatory and outcome variables. The non-linearity is modelled through smoothing functions – splines (f_1,…, f_l in Eq. (1)). The splines are sums of weighted basis functions with the estimated coefficients used as the weights (Wood, 2017). The number of basis functions to be included in the model is selected for each covariate by the researcher and determines the degree of flexibility of the relationship with the outcome variable. We used effective degrees of freedom (EDF) to check if the non-linear impact of covariates on the outcome variable is necessary. The EDF = 1 is an equivalent to a linear distance decay functions (due to the using logarithm of dependent variable in our case it is an equivalent of log-linear relationship), EDF > 1 and ≤ 2 corresponds a weak non-linearity, while EDF > 2 indicates a highly non-linear distance decay functions (Zuur et al., 2009).

In Eq. (1) spatial autocorrelation is allowed via a spatially-correlated error term with the estimated parameter λ. In addition, in this model we controlled for the spatial heterogeneity of apartment prices using spatial fixed effects and allowed for temporal dynamics by using a set of dummies for quarterly apartment sales. The details for choosing spatial weight matrix W and spatial fixed effects were presented in ESM Section 2.

The sptpsar package for the development of semiparametric spatial and spatio-temporal econometric models in R was used to estimate PS-SEM (Basile et al., 2014; Montero et al., 2018). The coefficients of PS-SEM were estimated using restricted likelihood maximization method.

In addition to the PS-SEM we also estimated: 1) a non-spatial linear regression model, 2) a linear regression model with additional spatial fixed effects, 3) a spatial error model, 4) a spatial smooth gradient model, and 5) a spatial smooth gradient model with additional spatial fixed effects. For more details, see the Section 2 of the electronic supplementary materials (ESM). These models were treated as alternatives to the PS-SEM in terms of the way they control (or not) for spatial autocorrelation. The results from these alternative models help us to choose the most appropriate structure of spatial autocorrelation and heterogeneity in PS-SEM. Their analysis helps understand why the PS-SEM was chosen as appropriate modelling technique for out data.

4. Results

4.1. Penalized spline spatial error model

The results for the PS-SEM estimates are presented in Table 2 and Fig. 2. For structural, noise and socioeconomic index, the network distance is not measured, hence linear coefficients are represented in the upper panel and significance of distance decay functions of environmental/walking distance variables are presented in the lower panel of Table 2.

Coefficient estimates for the structural variables follow intuition and previous research. A price premium is given for higher floor level, presence of elevator, more toilets and a new construction and/or renovation (last renovation or construction year). The model also shows that smaller area apartments have higher square meter prices, which can in part be explained by fixed transaction cost (Dahlman, 1979; North, 1992), as well as a pricing strategy where the price per unit area for the bigger flats is slightly lower than for smaller apartments (Mok et al., 1995).

The socioeconomic index, a proxy variable for neighbourhood demographic composition, shows a positive correlation with prices, in line with previous research (Mathur, 2014; Poudyal et al., 2009b). Dummy variables for modelled noise levels from 55 dB-64 dB and 65 dB and above were found as statistically insignificant when we control for spatial autocorrelation of error term (see ESM Table 5).

The PS-SEM has the highest goodness-of-fit (AIC) in comparison to alternative models such as spatial error model or spatial smooth gradient model (ESM Table 5). Moran's I test for PS-SEM residuals informs indicates that they are not spatially correlated. The estimated parameter λ, which captures spatial autocorrelation in PS-SEM, is positive and statistically significant, indicating that effects of spatially-correlated omitted variable(s) have been identified and controlled for.

4.2. Distance decay of property prices to walking distances

Walking distance variables are presented with EDF in the lower panel of Table 2. The semi-parametric modelling of distance decay functions is reported graphically in Fig. 2. The distance decay curves depict predicted price per square meter for the median sale prices on the y-axis and the walking distance in meters on the x-axis. The EDF estimated from PS-SEM are above 2 for each distance decay functions indicating a high non-linearity of an impact of distance to amenity on sale prices (Zuur et al. 2009). The parametric part of the majority of distance decay functions are not statistically significant. Only the parametric part of distance decay to small, medium and large parks are significant. For these greenspaces distance decay functions distinguish parametric and semi-parametric features (Table 2).

Walking distance to large parks displays non-linear distance decay in the PS-SEM plot only beyond about 800 m. The plot for medium parks shows increasing price with distance, but this finding is not significant (the 95% confidence interval lies outside the plot range in the figure). For medium parks the slope varies from positive to negative between models with different specifications of the spatial component, suggesting correlation with omitted spatially-correlated variable(s) (see ESM Table 5). At distances of up to about 100 m from small parks, the PS-SEM

Table 2 (upper panel)
Results from the penalized spline spatial error model (PS-SEM):

Variable	Estimated coefficient	Std. Error	P-value
Const.	12.722***	0.361	0.000
Last renovation 2000–2009	0.065***	0.005	0.000
Last renovation after 2009	0.080***	0.006	0.000
Top floor	−0.030***	0.000	0.000
Elevator	0.031***	0.004	0.000
Number of WCs	0.076***	0.003	0.000
Ln(Living space)	−0.267***	0.003	0.000
Socioeconomic index	0.001**	0.000	0.023
Noise 55–64	−0.005	0.004	0.198
Noise 65+	−0.001	0.005	0.855

Significant at: *** 0.01; ** 0.05; * 0.1.

Table 2 (lower panel)
Results from the penalized spline spatial error model (PS-SEM): semi-parametric distance decay functions.

Variable	Parametric part of function	Semi-parametric term (EDF)
f_1 (Distance to commercial amenities)	1.252	5.234
f_2 (Distance to cultural amenities)	−0.478	21.483
f_3 (Distance to metro)	−0.345	8.776
f_4 (Distance to highway)	2.002	8.417
f_5 (Distance to school)	−0.328	5.434
f_6 (Distance to fjord)	−1.366	12.961
f_7 (Distance to Marka N)	−0.528	7.282
f_8 (Distance to Marka E)	−0.112	3.872
f_9 (Distance to pocket parks)	0.072	6.825
f_{10} (Distance to small parks)	−0.574***	8.680
f_{11} (Distance to medium parks)	3.635**	5.957
f_{12} (Distance to large parks)	0.725***	6.257
Time fixed effects	Yes	
Spatial fixed effects	Yes	
λ	0.404***	
AIC	−30,020	
Moran's I test	−0.001	
N	41,805	

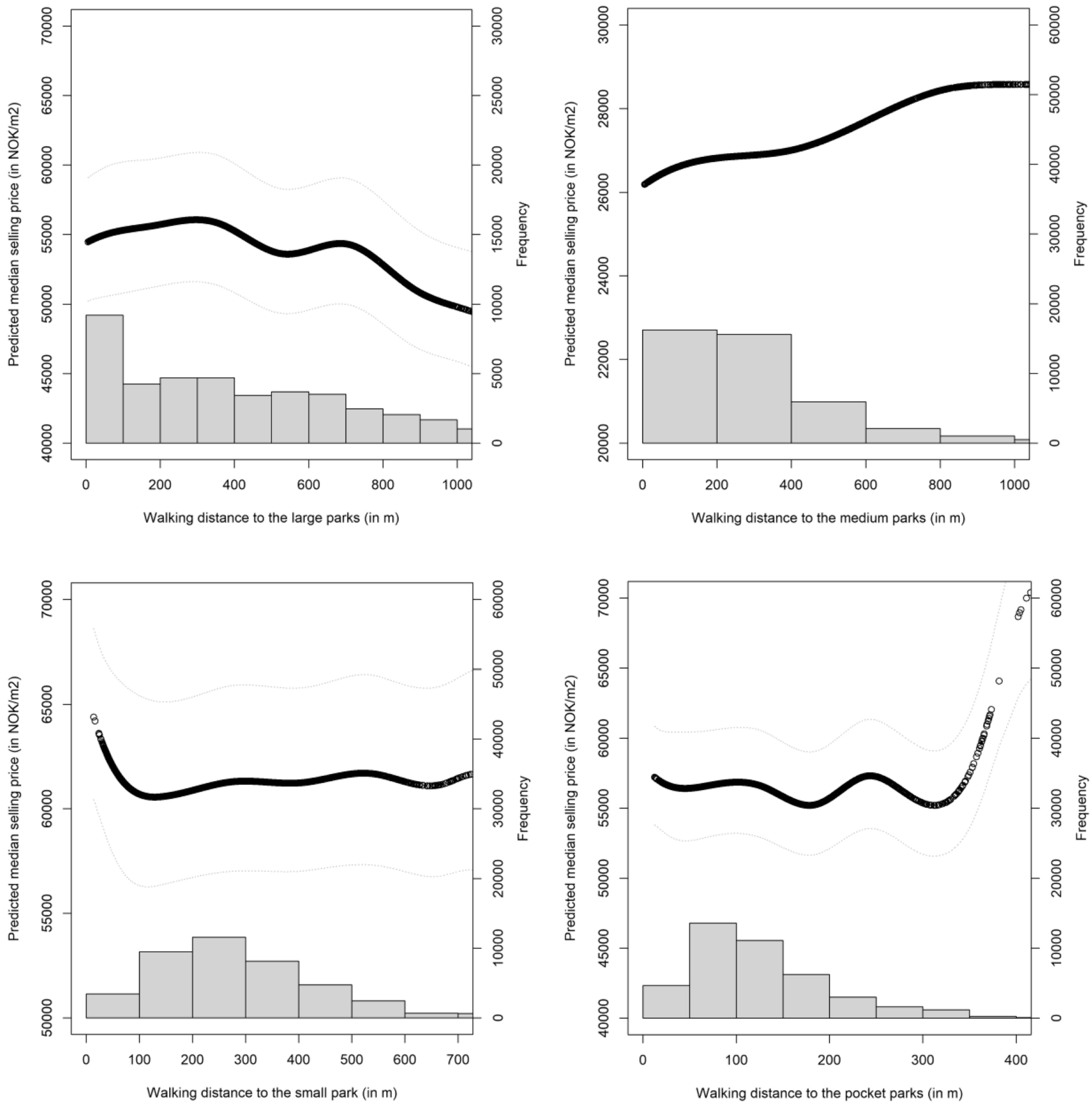

Fig. 2. Estimated distance decay functions (Eq. (1)). The 95% confidence intervals are shown as light dotted grey lines. In some plots uncertainty is so high that confidence bounds lie outside the plot range. Histograms of the individual walking distance variables are added on the right y-axis.

shows distance decay effects, but not beyond. There is no meaningful distance decay in PS-SEM for pocket parks. A slight negative trend is observed for the mass of sales points (see histogram on the right y-axis) up to 200 m. In contrast, using simple log–log models produces consistently negative, statistically significant estimates (ESM Table 5).

Walking distance to the peri-urban Marka forests on either side of the city shows monotonically decreasing prices which flatten out above 2 km for Marka East and 3 km for Marka North. Distance decay is negative and statistically significant in the log–log SEM model for both peri-urban forests (ESM Table 5). Only distance decay for the East forest is significant in the PS-SEM. Walking distance to the fjord shows significant distance decay over the nearest 1500 m. This is consistent with the results obtained using alternative models which all estimated the distance to fjord as statistically significant with a negative sign.

Walking distance to primary schools in all log–log models was found as statistically significant with negative sign of estimates. The sale prices decrease with an increase of distance to primary schools mostly up to 400 m. Walking distance to cultural amenities does not follow expected patterns of distance decay, as it shows an expectation that prices increase with distance, while the commercial amenities variable has a flat distance decay function. Also, all of the alternative models, which use log–log functions, would indicate that the decrease of distance to cultural or commercial amenities results in a decrease rather than an increase of sale prices.

Walking distance to metro stations shows no significant pattern within the walkable range. Highway entrance points are a disamenity, also in the log–log models (ESM Table 5).

4.3. Robustness checks

Using the data-driven PS-SEM approach we find some of non-linear distance decay functions (Fig. 2) that appear to run counter to the expectations from much of the HPM literature. Especially, when it comes to distance to medium parks the marginal willingness to pay increases with distance to these parks rather than decreases, as expected. Visual inspection of the distance decay functions in Fig. 2 shows that the

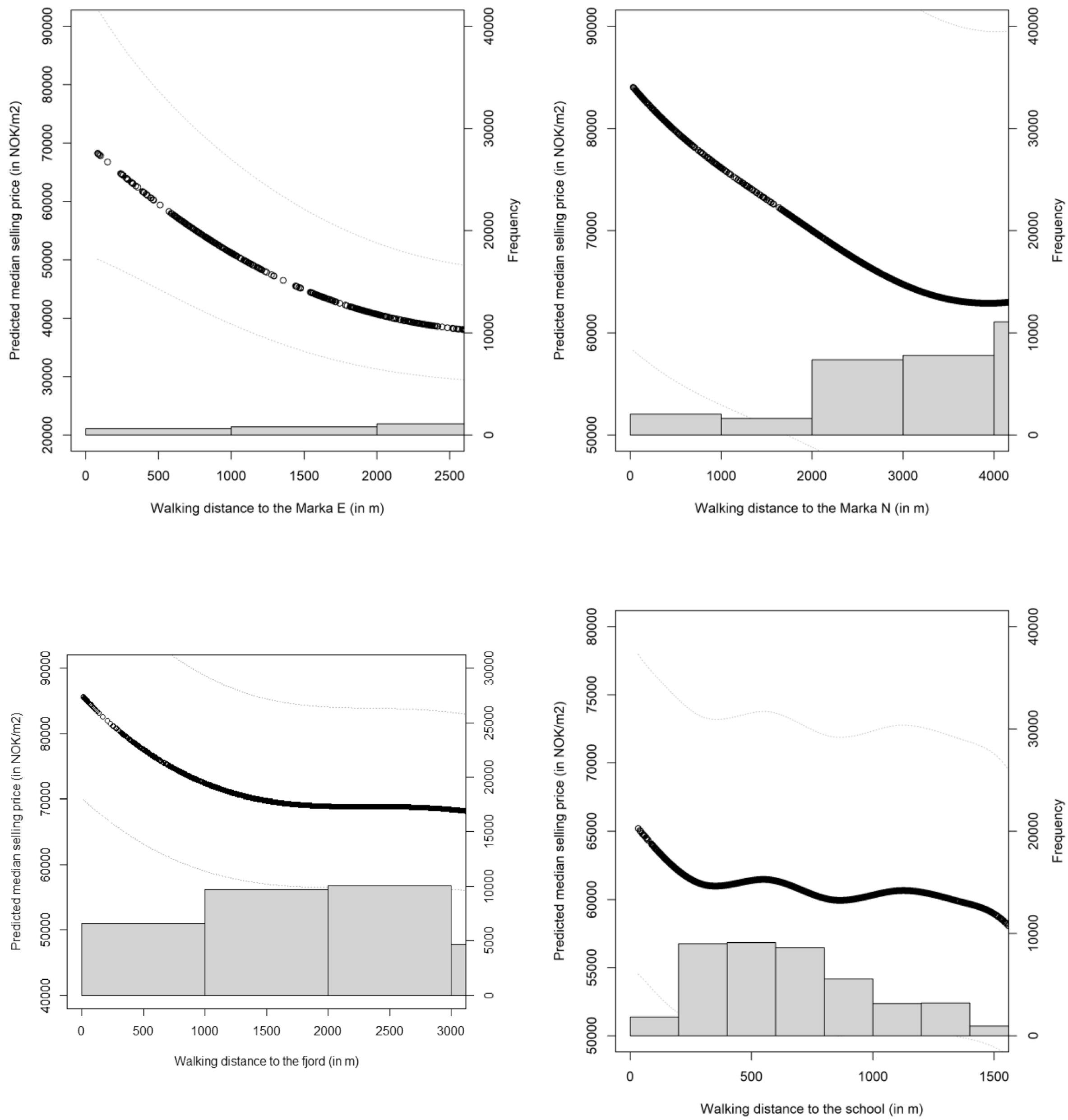

Fig. 2. (*continued*).

counter-intuitive positive slopes of implicit property prices for greenspace are local and not significant over the distance ranges of the variables. For further documentation we carried out extensive robustness checks on the PS-SEM, including (i) alternative econometric approaches with the emphasis on the correct inclusion of omitted spatially-correlated variable(s) bias and (ii) alternative functional forms for accessibility.

4.3.1. *Alternative econometric approaches*

To assess robustness, we estimated other econometrics models, described detailed in ESM Section 2. We started from the non-spatial linear regression model for which we run diagnosis towards an identification of spatial autocorrelation and heterogeneity. For the former we applied Moran's I test and Lagrange Multiplier tests. The Moran's I test on the linear regression model residuals shows the presence of spatial autocorrelation (ESM Table 3). Using Moran's I we tested eight different spatial weight matrices with the global, semi-local and local structure of relations between sales points (Chen, 2012). We found that the highest Moran's I coefficient (0.26) is for the spatial weight matrix with 3 nearest neighbours (KNN = 3) (Kooijman, 1976). This informs us that we have local spatial autocorrelation in the model. For the KNN = 3 spatial weight matrix we conducted the Lagrange Multiplier tests (ESM Table 2) which suggested that the spatial autocorrelation instead of spatial dependence is necessary to control in our model. One of the potential explanations why local spatial autocorrelation was found in this model could be the omitted structural characteristics of housing stock such as a building's condition.

To check spatial heterogeneity, we estimated a non-spatial linear regression model with spatial fixed effects. We tested three different ways of grouping the city into spatial units (ESM Table 4). Based on the R_{adj}^2 we decided that adding spatial fixed effects for 3-digit postcodes is necessary to control for spatial heterogeneity. The inclusion of those fixed effects increased the R_{adj}^2 more than any other spatial fixed effects – from 52% (lack of spatial fixed effects) to 61%. We used spatial fixed effects in all the next models. This is in the line with others (Heyman and Sommervoll, 2019) who found using the hedonic pricing model in Oslo

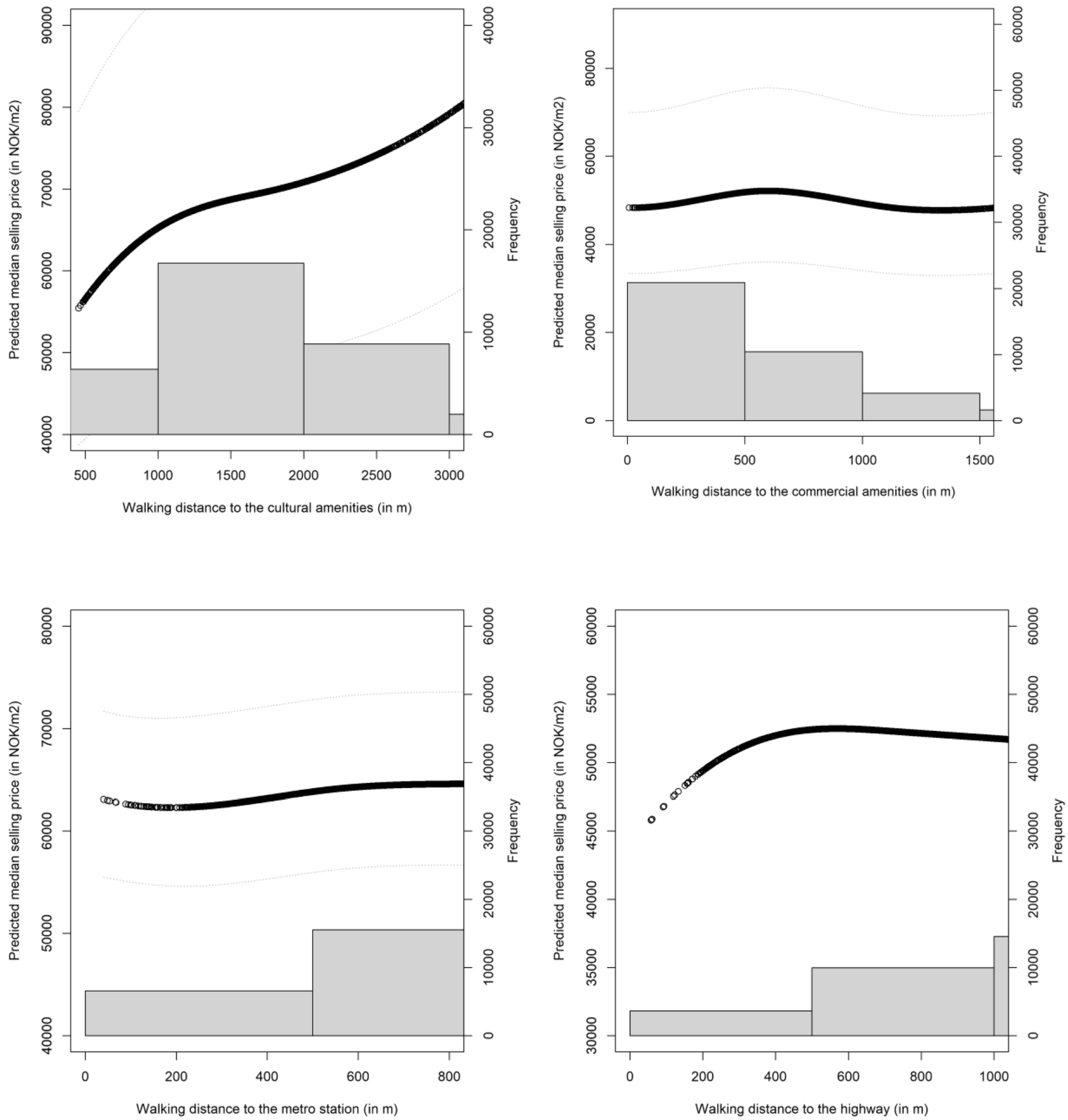

Fig. 2. (*continued*).

that the 3-digits postcodes improve the goodness-of-fit and enables capturing the local sale prices fluctuations.

In addition, we conducted the Box-Cox test to evaluate if any transformation of our dependent variable is required in the further analysis (Davidson and MacKinnon, 1985). We obtained $\lambda = 0.06$ which suggests that the logarithmic transformation of sale prices is necessary. Therefore, in all models we used natural logarithm of sale prices. Also, following Heyman and Sommervoll (2019), who estimated the hedonic pricing model for Oslo using OLS and obtained goodness-of-fit around 81.5% for sale prices, we tested how much the goodness-of-fit of our basic model (without non-linear distance decay functions, but including spatial autocorrelation) would differs if we would use sale prices instead of sale prices per square meter (see Section 3.1). We found that the model with sale prices as the dependent variable is comparable when it comes to goodness-of-fit with those proposed by Heyman and Sommervoll (2019) and have $R_{adj}^2 = 82\%$. Finally, for the non-spatial linear regression model (ESM Table 2), we found that multicollinearity is not expected to be a problem as the variance inflation factor (VIF) is consistently below the suggested value of 5 (Rogerson, 2001).

To address spatial autocorrelation, we estimated not only PS-SEM, but also four additional models representing different approaches to deal with spatial autocorrelation (see ESM Section 2). This included models which were previously found to have limited ability to control spatial autocorrelation such as model with additional spatial fixed effects. We would expect that only the spatial error model (SEM) enables fully controlling for spatial autocorrelation. The SEM has the highest goodness-of-fit measured by AIC and Moran's I test for its residuals shows no spatial autocorrelation. Other models, including spatial smooth gradient model, reduced the Moran's I coefficient, but could not fully eliminate the autocorrelation.

Interestingly, models with additional spatial fixed effects (Eq. 3 and 6) for within-building interactions, reduced the Moran's I more than pure spatial smooth gradient model (excluding SEM). Although there is no doubt among spatial econometricians that spatial fixed effects cannot fully remove spatial autocorrelation from the model (Anselin and Arribas-Bel, 2013), the only exception is the group-wise spatial autocorrelation in which all spatial observations that are members of the same group influence one another in the same way. The reduction of Moran's I coefficient in this case is in the line with the argument that the source of the spatial autocorrelation in our model is perhaps the omitted spatially-correlated variable(s) such as missing quality of the housing stock.

The results from the estimation of alternative models show the superiority of SEM over the other modelling strategies. Therefore, the extension of SEM towards its semi-parametric version (PS-SEM) was applied as the final model. The comparison of PS-SEM with SEM shows that PS-SEM has higher goodness-of-fit than SEM. Also, the EDFs supports the conclusion that going beyond the log–log function offered by SEM, towards semi-parametric non-linearity in PS-SEM is an appropriate direction of analysis. Both PS-SEM and SEM control for spatial autocorrelation in the same way and could be used for more detailed comparisons.

Interestingly, the estimates for distance to amenities vary between alternative models. This suggests that the distance-related explanatory variables are the most susceptible to the way we control for spatially-correlated omitted variables. The use of non-spatial models may lead to misleading conclusions regarding the impact of the amenities on sale prices. While the estimates for distance to commercial and cultural amenities remains the same across models, other distance-based variables switch their signs or lose significance. This is especially observed for distance to small and medium parks. This suggest the necessity to interpret the findings with the greatest caution as they may reflect the spatial instability of the estimates. More detailed comparison of the results form alternative econometric approaches are provided in ESM Section 2.

4.3.2. Alternative functional forms for accessibility

We checked alternative approaches to capture the non-linearities in the hedonic pricing models with the use of a stepwise function and alternative measure of greenspace proximity using the proportion of greenspace within different circle buffers from the residence (ESM Tables 6 and 7). In particular, we specified a stepwise distance decay function, for the SEM, as the interaction between logarithm of distance to greenspace and a set of dummies reflecting discrete distance segments, instead of a single continuous distance variable as above.

The estimates of the stepwise distance decay function are interpreted similarly to log–log estimates, however they are valid for the given distance range. While the log–log estimate can be treated as an "average" impact on all sale prices, the stepwise distance decay function decomposes this "average" into distance ranges. This means that estimates for stepwise distance decay function would vary from the log–log estimate and increase/decrease or remain insignificant depending on the shape of distance decay function. However, the estimation of stepwise distance decay requires a series of distance-based variables, increasing the possibility of potential collinearity with other covariates, including spatial fixed effects.

In addition, in comparison to a semi-parametric distance decay functions obtained from PS-SEM, a stepwise decay function is still just an average. It could be valid if there is no local variation in distance decay function and the frequency distribution of observations for different distance thresholds is similar. However, in our case, there is variation in the number of property transactions for different walking distances to greenspace, and variation in the structure of street networks and accessibility. This leads to local variation in each distance decay function. For this reason, the average effects in the logarithmic distance decay models are not fully consistent with the estimates for stepwise distance decay functions while the latter do not fully reflect the shape of semi-parametric distance decay functions in the PS-SEM.

The stepwise averages of the distance decay function (ESM Table 6) are only partly consistent with the non-linear distance decay functions of the PS-SEM and the log–log SEM estimates. For example, the estimates for ln distance to pocket greenspaces was found to be negative and statistically significant (-0.011 with p-value < 0.01), as expected, in SEM model. The estimated PS-SEM semi-parametric distance decay function for pocket greenspace shows no meaningful distance decay, especially after a threshold at 200 m (most observable decrease is up to 50 m). The estimates for corresponding stepwise distance decay function is more in line with expectations. The estimates for the distance up to 50 m has the highest absolute value. Within the distance of 50 m an increase of distance to pocket greenspace by 1% results in a decrease of sale prices per square meter by 0.018% (*ceteris paribus*). This effect is lower in absolute value for the distance range 50–100 m (0.015%) and then decrease again up to 200–400 m. Although the stepwise distance decay function indicates that after 200 m the impact of pocket greenspace is still statistically significant, it is smaller especially in comparison to effect within distance up to 50 m.

The estimates for medium greenspace are statistically significant but positive, both in log–log SEM and in model with stepwise distance decay function. The PS-SEM shows that these counterintuitive effects are not significant.

The stepwise distance decay function for small greenspace shows that the highest reduction of sale prices with increasing distance to small parks is observed up to 100 m. This impact remains statistically significant and negative for the other distance ranges, however it systematically decreases. In contrast, in PS-SEM the visual inspection of semi-parametric distance decay function gives more unambiguous conclusion about the threshold distance. Importantly, the distance thresholds used to create stepwise distance decay functions were based on the inspection of PS-SEM results. What does this mean? Without this knowledge the researcher who wants to detect the thresholds has to do it by testing various thresholds set up a priori or based on the previous findings. In contrast, with the PS-SEM, the stepwise decay functions might be used to evaluate the robustness of the results.

While the results from log-log, stepwise distance decay and semi-parametric distance decay functions produce a partly consistent picture of the greenspace "premium", models using aggregated greenspace in buffers are in contradiction (ESM Table 7). The estimates for density of greenspace in the circle buffers are expected to be statistically significant and positive with the systematic decrease of estimates for the buffer >100 m, 100–250 m, 250–500 m and 500–1000 m. However, these estimates are not statistically significant and those which were found to be significant have negative sign. The negative sign means that with the increase of greenspaces in the circle buffer (for example from 100 to 250 m from the sale point), the sale prices decrease. These results indicate the need to disaggregate greenspaces in hedonic pricing models. It is because, as our study demonstrates, not all greenspaces generate price "premium" and some of them may act even as disamenities for real estate buyers (Łaszkiewicz et al., 2019).

5. Discussion

Using PS-SEM to estimate the non-linear distance decay functions between apartments' prices and walking distance to amenities provides a novel and flexible approach to valuing greenspace. The combination with advanced spatial analysis enables PS-SEM to capture peoples' spatial preferences in a more detailed way than in previous HPM literature. In the following, we discuss some urban planning and policy implications of the results.

5.1. Accessibility thresholds for different greenspace types

The walking distance variables related to greenspace show varied results across types of greenspace. This is similar to the results provided by (Czembrowski and Kronenberg, 2016) who found that different types of greenspace exert different impacts on property prices. A review of US studies found that most of the impact on sale prices by greenspace is generated within 400 metres (Crompton and Nicholls, 2021). This range is lower than what we find for Oslo's peri-urban forests, large parks and coastline.

The walking distance to the peri-urban forests of Marka East exerts a sigificant influence on property prices, while the relationship is not significant for the peri-urban forest to the North of the city. There is indication of distance decay after a threshold distance for large parks, indicating that commonly used logarithmic assumptions about distance decay could be incorrect for specific categories of greenspaces. There is also some support that distance to small parks has a significant effect on prices within the proximity of approximately 100 m, which follows previous research (Millward et al., 2013).

Yang and Diez-Roux (2012) showed that walking distances around 1.5 km are common for recreational destinations. Small and pocket parks follow an expected pattern of distance decay for most alternative econometric models (see ESM). Plots for PS-SEM (Fig. 2) show distance decay effects to be non-linear close to residences. Lacking significance of smaller greenspace accessibility across longer distances may be because 98% of residences have access at least to small parks (>1000 m2) within close walking distance (300 m) (Kommune, 2021). The significant results for coastline, peri-urban forest and large parks emphasize that for these large blue-green spaces access is more unequally distributed across the city, leading to significant and different distance decay functions. There is greater willingness to walk further for larger greenspaces because they offer a greater diversity of use opportunities (Massoni et al., 2018).

How are these results relevant for urban planning in Oslo? The significant distance decay effect for large parks above 700 m is quite compatible with Oslo's Green Plan recommendations. Weak or lacking distance decay for medium, small and pocket parks is an indication that the Green Plan's objective of residential walking access to greenspace has also been environmentally just as property values do not generally discrimante residents' neighbourhood greenspace access (Suárez et al., 2020). The fewer large parks, coastline and peri-urban forest provide higher multifunctionality (Massoni et al., 2018) are also unequally distributed. More unequal distribution of large greenspaces provides a plausible explanation for higher likelihood of observing significant distance decay effects. Furthermore, the lack of distance decay effects within walking distance of the large parks may suggest that accessibility to smaller parks is good within that range. A new finding for Oslo's Green Plan is that access to the fjord is significant within about 1500 m. This could be due to decreasing fjord visibility with distance, whereas distance decay to parks and forest is due to walkability. Other studies have found similar distance decay for access to water and beaches (Millward et al., 2013).

5.2. Generalizing hedonic pricing results for urban ecosystem accounting

The modelling results emphasize the importance of using network walking distances in order to capture non-linear effects of distance in hedonic pricing models. Euclidean distance underestimates actual walking distance to reach greenspaces. An average Euclidean distance from sale points to the nearest pocket park is 25% lower than network distance. Similar underestimation of distance is observed for other greenspaces. For small parks the underestimation caused by using Euclidean instead of network distance is 24%, for medium parks 33% and for large parks 23%.

Using Euclidean distance specifications and OLS models without spatially-correlated error term Traaholt (2014) observed distance decay in implicit property prices for greenspace access, but this seems to be driven by the variable and model specification. While Euclidean distance to greenspace variables are largely not significant in the non-spatial GAM model used by Traaholt (2014), using PS-SEM we observe non-linear distance decay in property prices relative to walking distance for some types of greenspace. What does it mean in the broader perspective? Insufficient or lack of control for spatially-correlated omitted variable(s) may lead to misleading conclusions. As we demonstrate in the robustness analysis, especially distance-related variables are highly sensitive to the way the spatial effects are included in the model. What is more important, the simple non-spatial models might wrongly indicate statistically significant effects, even with signs of parameters that are consistent with our expectations, just because of the way those variables are correlated with omitted spatial variable(s). Therefore, caution is needed in using any single modelling strategy and an extensive robustness analysis is required to confirm the consistency of results.

Are our findings generalizable? With a large number of greenspaces of different sizes within the built zone, and peri-urban Marka forests immediately adjacent to and completely encircling the built zone, Oslo may be somewhat atypical compared to more densely built capital cities (Łaszkiewicz et al., 2021). We speculate that the close pedestrian proximity to a large variety of greenspaces across the city mean that urban greenspace recreation value is harder to observe in property prices than in most of the cases documented in the HPM literature. The results in this paper confirm that the linear scaling and aggregation of OLS estimates by Barton et al. (2015) was not a reliable approach to valuing most greenspace types in Oslo, even if the purpose is for general awareness-raising requiring less reliability. In Oslo other methods for identifying the economic values of urban greenspace amenities are needed.

Our documentation of robust non-linear distance decay effects using the PS-SEM provides a general caution against using HPM valuation estimates for greenspace policy analysis that are based on linear distance and smooth log distance decay specifications. The caution is also relevant for future thematic urban ecosystem accounts (United Nations, 2021). National Statistical Offices commissioning hedonic pricing methods should measure pedestrian network distances and should check robustness to spatial heterogeneity in different urban areas using sGAM models.

6. Conclusions

This paper investigates the relation between walking accessibility to amenities from greenspaces on apartment prices in Oslo, controlling for structural effects and network pedestrian distances to greenspace and other urban amenities. We demonstrate non-linear relationships between walking distances to some amenities and property prices. Distance decay in property prices is non-linear, sometimes displaying thresholds that depend on the size and type of greenspace. Our composite indicators of cultural and commercial amenities are not sensitive to the spatial processes defined in the PS-SEM. We carry our extensive checking of modelling robustness and find that non-linear distance decay effects are robust in the Oslo case. We discuss the advantages of the PS-SEM, in particular its data-driven specification of distance decay functions, rather than using a priori assumptions required by other econometric modelling techniques. Notwithstanding the idiosyncrasies of Oslo's greenspace configuration, we argue that the PS-SEM is a generally applicable approach to control for non-linear distance decay.

The findings of significant thresholds in modelling hedonic price decay in walking distance to greenspace in PS-SEM could be used by planners to assess distributional impacts and inform standards on maximum walking distances to greenspace for new property developments. Significant effects of publicly managed parks on property prices may also provide additional support for public park maintenance efforts. If significant non-linear distance decay functions are observed, they will also provide more accurate value aggregation for the purpose of urban planning policy and ecosystem accounting.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2021.101394.

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