Regional Science and Urban Economics 73 (2018) 127–142

Contents lists available at ScienceDirect

Regional Science and Urban Economics

journal homepage: www.elsevier.com/locate/regec

Eliciting preferences for urban parks

Toke Emil Panduro[a,*], Cathrine Ulla Jensen[a], Thomas Hedemark Lundhede[a,b,d], Kathrine von Graevenitz[c], Bo Jellesmark Thorsen[a,b]

[a] Department of Food and Resource Economics, Faculty of Science, University of Copenhagen, Rolighedsvej 23, 1958 Frederiksberg, Copenhagen, Denmark
[b] Center for Macroecology, Evolution and Climate, University of Copenhagen, Rolighedsvej 23, 1958 Frederiksberg, Copenhagen, Denmark
[c] Department of Environmental and Resource Economics, Centre for European Economic Research (ZEW), P.O. Box 103443, 68034, Mannheim, Germany
[d] Centre for Environmental Economics and Policy in Africa, Department of Agricultural Economics, Extension and Rural Development, University of Pretoria, South Africa

ARTICLE INFO

Keywords:
Hedonic house price model
Green space
Preference heterogeneity identification

ABSTRACT

The hedonic pricing method has been used extensively to obtain implicit prices for availability of urban green space, but few have obtained households' preference parameters. We elicit preferences and estimate willingness to pay functions for park availability in Copenhagen using an approach that places identifying restrictions on the utility function. We do this for two different measures of park availability and examine sources of preference heterogeneity. We find that the implicit price of another hectare of park within a 1000 m radius is 53.25 EUR per ha per year for the average apartment corresponding to an increase in annual rent of 0.33% per additional ha. For reducing distance to the nearest park by a meter, the price is 0.59 EUR per meter per year, corresponding to an increase in annual rent of 0.03‰ per meter. We apply our results to a policy scenario reducing the park area available in an area of central Copenhagen and show how estimates of aggregate welfare changes are highly sensitive to the measure of park availability applied. The findings stress the importance of paying attention to how public goods are defined when undertaking welfare economic policy analyses.

1. Introduction

Parks provide recreational opportunities for urban residents and visitors. Urban green spaces furthermore provide climate regulation functions, harbor biodiversity and provide other ecosystem services. As it is a public good, the market is unlikely to provide green space in optimal quantities without public intervention. Urban authorities can ensure provision through, e.g., regulation of private developers or by ensuring themselves that land is set aside. However, in the absence of thorough insights into the values of urban green space, the need for such regulation may be neglected whenever new neighborhoods are planned and developed.

For that reason, urban and environmental economists have undertaken numerous studies estimating the value of urban parks and other green spaces to provide a better basis for the regulation of the urban development. To that end, they have used various environmental valuation techniques, notably Rosen's (1974) hedonic pricing framework, extensively. Rosen showed how, under suitable assumptions, one can obtain implicit prices of the different characteristics of a property from the hedonic price function, including the availability of various public goods like a park. Numerous studies have used this approach to estimate the importance of green spaces and parks as more spatial data, and computational capacity has become available, e.g., Tyrväinen and Miettinen (2000) and Lake et al. (2000) and new applications are added regularly (e.g., Sander et al., 2010; Panduro and Veie, 2013: Franco and Macdonald, 2018), including to value sunshine exposure in cities (Fleming et al., 2018).

The hedonic price function recovered in the first stage of the hedonic method relates each attribute to the property price at the given market equilibrium. However, the information revealed about the preferences of households is limited to their willingness to pay the implicit market price for the amenity in question, and thus only welfare effects of marginal changes in an amenity can be evaluated. For amenities such as urban parks, urban land use policy may sometimes cause changes that are non-marginal and discrete changes for the household. The analysis of welfare implications of discrete changes requires estimates of the households' preference parameters. This crucial information can be obtained by completing the second stage of the hedonic analysis outlined by Rosen (1974). However, comparatively few studies have undertaken the second stage and only one of these addresses the demand for urban parks

* Corresponding author.
E-mail address: tepp@ifro.ku.dk (T.E. Panduro).

https://doi.org/10.1016/j.regsciurbeco.2018.09.001
Received 19 January 2018; Received in revised form 5 September 2018; Accepted 5 September 2018
Available online 11 September 2018
0166-0462/© 2018 Elsevier B.V. All rights reserved.

(Poudyal et al., 2009). Undoubtedly, one of the reasons for this gap in the literature is the difficulty in obtaining good instruments for handling the endogeneity of the level of amenities chosen by households, resulting from taste-based sorting. When applying multiple markets as instruments as, e.g., Poudyal et al. (2009), spatial sorting across markets of households is assumed not to occur, a strong and restrictive assumption in many cases. In this study, we apply a different identification approach, as we rely on restrictions on the utility function, an approach suggested by Bajari and Benkard (2005). While not perfect, their approach represents a simple and useful framework suited for cases like ours. It does not require restrictive assumptions on sorting behavior nor on the distribution of idiosyncratic taste heterogeneity making it well-suited for our study.

The estimation of preference parameters for urban amenities and hence welfare gains and losses resulting from non-marginal changes are sensitive to the way in which the public good attribute is measured and modeled (Ahlfeldt, 2011). Policy evaluation should address this issue explicitly and carry out a sensitivity analysis. The literature applies a plethora of different specifications of urban green space goods, and there is no conclusive evidence on what the most appropriate measure is in a hedonic context.

We aim to further the development of the field by applying the alternative approach developed by Bajari and Benkard (2005), to recover preference parameters, introducing this method in the environmental economics literature on green space. Bajari and Kahn (2005) first applied it to study preferences for racial composition in neighborhoods. Earlier related work by Chattophadyay (1999) uses different functional form assumptions to identify preferences for air quality. We apply the Bajari and Benkard (2005) approach to study preferences for urban park availability in central Copenhagen, Denmark. We decompose preference heterogeneity into heterogeneity related to observable socio-demographics and remaining idiosyncratic taste. We further assess the impact of using two different but commonly used park availability measures, to investigate how sensitive estimates of the aggregate policy-induced welfare changes and their distribution are to the specification of the amenity in question.

2. Previous work

2.1. Uncovering the willingness to pay function

There is an abundance of studies applying GIS-based data and first stage hedonic regression techniques of varying sophistication to uncover implicit prices for goods like urban parks, and only a few attempting to obtain preference parameters of households or estimate demand functions. The reason is that we only observe a single transaction for each household in a typical hedonic study, and households are likely to sort themselves across space according to preferences. As a result, we may observe two seemingly identical households buy properties with vastly different amounts of the amenity, due to unobservable idiosyncratic taste. As explained in detail already by Bartik (1987) and Epple (1987), fitting an inverse demand curve across households is likely to result in biased parameter estimates unless taste-based sorting is accounted for.[1]

Different approaches to tackle this issue have been suggested. The first is the construction of instrumental variables through analysis of multiple markets. When using multiple markets to create instruments, preferences are assumed to be identical across markets, conditional on socio-demographics, and no sorting is assumed between markets.[2] Thus, cross-market variation in prices is assumed to arise solely from differences in the supply of housing with different attributes. This allows a market indicator variable to function well as an instrument. Poudyal et al. (2009) used this approach in a second stage hedonic regression and applied cluster techniques to identify sub-markets. Brasington and Hite (2005) used the approach to uncover preference parameters for environmental qualities as well as school quality. Preferences for other urban (dis-) amenities like noise have been uncovered by Day et al. (2007) using a related approach based on spatially lagged implicit prices across distances as instruments. For multiple markets within the same urban area, it is hard to argue that no taste-based sorting takes place between markets, see, e.g., Zhang et al. (2015) for an approach specifically addressing such imperfect instruments in a hedonic context. Instruments based on household preferences for other goods are also unlikely to be exogenous to the choice of housing.

An alternative approach to recover preference parameters, which we use, obtains identification by imposing restrictions on the utility function. This approach was first applied by Chattophadyay (1999) in an analysis of air quality in Chicago. Later Netusil et al. (2010) applied the same approach to study preferences for tree canopy cover in an area of Portland, Oregon. Bajari and Benkard (2005) expanded this framework, and Bajari and Kahn (2005) applied their approach to the racial composition of neighborhoods. Thus, the approach has been used to a very limited extent in environmental economics (von Graevenitz, 2018; Jensen et al., 2016a).

A clear advantage of this approach is its transparency in contrast to the instrumental variable approaches, where the necessary properties for instruments to be valid can be hard to satisfy in practice. Empirical data can show substantial spatial sorting (Jensen et al., 2016a; b), with respect to preferences for green spaces, as well as a number of other possibly correlated preferences. Restricting sorting behavior, e.g., by using instruments based on market segments seems inconsistent with this observation. Furthermore, while the Bajari-Benkard approach requires the analyst to restrict the shape of the utility function, it does not place any constraints on the distribution of preferences. This property is especially desirable for policy analyses exploiting preference heterogeneity.

2.2. Measures of urban green space in hedonic valuation studies

Few fields have been as responsive to Rosen's (1974) hedonic pricing framework as the environmental valuation field studying the value of urban green spaces. The number of studies investigating the implicit price of various aspects and types of urban green space is impressive, and we offer only a partial coverage focusing on the variation in measures of urban green space availability that have been applied in the literature. All of the studies, with one exception, rely solely on first stage hedonic analysis.

In general, most measures have focused on two aspects of supply; distance to green areas and the amount of green areas. Proximity, represented by various distance measures from the property to one or more green areas, has often been used, e.g., Lake et al. (2000) used measures of walking distance to the nearest park in a UK study of house price determinants, and Mansfield et al. (2005) applied various measures, including linear distance to urban and peri-urban forest lands. The other measure often applied is the amount of green area available, in either absolute terms, (e.g., size of the nearest green area, area available within a given radius) or various relative measures of green space density within a radius of the property. For example, Kong et al. (2007) used density and patchiness measures of urban green space in combination with distance measures.

It is important to pay attention to how accessibility of amenities is modelled, as it affects hypothesis evaluation, as shown by, e.g. Ahlfeldt (2011) and Sadayuki (2018), and also affects policy evaluation, as we will show. Therefore, we evaluate the effect of specification using a measure of proximity to the nearest urban park within, a measure of the total area of the urban park available, alone and in combination.

[1] The literature on identifying and estimating demand schedules has grown continuously; see e.g. Ekeland et al. (2004), Heckman et al. (2010), and Bishop and Timmins (2017).

[2] Ekeland et al. (2004) show conditions under which the MWTP function is identified in a single market.

3. Theoretical framework

Our estimation procedure involves three steps, parallel to Bajari and Benkard (2005) and Bajari and Kahn (2005). In the first step, we estimate a hedonic house price function; in the second step, we recover household-specific preference parameters, and in the third step, we decompose variation in preferences using observed socioeconomic characteristics.

A house is a composite good and can be described as a bundle of attributes, X_j, one attribute being access to green space. The price P_j of a house j in market equilibrium is a function of its attributes, $P_j(X_j)$.

Households obtain utility from consuming housing, X_j, and from all other goods described by a composite numeraire good, c_i. The annual flow of utility for household i living in house j is described by the utility function $U(X_j, c_i;\ \gamma_i)$ where γ is the household specific preference parameters. Each household spends its total annual income y_i on housing and all other goods and occupies only one house so that i and j are interchangeable. Utility is assumed separable in time. We can therefore model the choice of housing as a static problem (Bajari and Benkard, 2005).[3] We calculate the annual cost of housing from the transaction price at time of purchase. Assuming perpetual life for the house asset and multiplying the price with an asset return rate π suitable for the house asset; we converted the price to a perpetual annuity.[4] We set π equal to 5%. For comparison, the Danish Central Bank used a measure of the user-cost of housing of approximately 3% over the period, and the Danish Economic Council applied a user-cost rate of 3.7% in a study of road noise impacts in Copenhagen (von Graevenitz, 2018).

Households are assumed to be rational utility maximizers and choose their preferred housing bundle given their income and preferences for housing goods and all other goods. Thus, they face the following maximization problem where γ_i captures household specific preference parameters determined by socioeconomic characteristics of the household and inherent preference heterogeneity:

$$\max_{x,c} U\left(X_j, c_i; \gamma_i\right)\ s.t.\ y_i = \pi P_j\left(X_j\right) + c_i \tag{1}$$

For a housing bundle $j*$ to be the utility maximizing choice for household i the marginal cost for house characteristic k assuming a continuous good x_{jk} must equal the households marginal rate of substitution. The following first order conditions must hold at the optimum:

$$\frac{\delta\, U\left(X_{j*}\right), y_i - \pi P_{j*}\right)/\delta x_{jk}}{\delta\, U\left(X_{j*}\right), y_i - \pi P_{j*}\right)/\delta c_i} = \pi \frac{\delta\, P\left(X_{j*}\right)}{\delta x_{jk}} \tag{2}$$

The right-hand side of (2) is the implicit annual price recovered from the hedonic price function. The left-hand side is the household's marginal rate of substitution between the amenity and the numeraire good, which can be interpreted as the implicit price of the good. As we only observe one choice per household we only have one point on each indifference curve. Without further information about household preferences, we cannot make inferences about the (non-)marginal willingness to pay.

Bajari and Benkard (2005) obtain identification of household preferences by imposing a functional form for the utility function and assume weak separability in the k housing goods.[5] They suggest that one possible assumption for the utility function could be that the utility is logarithmic in housing goods and linear in consumption of the numeraire good. We adopt this assumption here and discuss the sensitivity of this choice later. This leads to the following utility function:

$$U\left(X_j, c_i; \gamma_i\right) = \sum_k \gamma_{ki} \log\left(x_{jk}\right) + c_i \tag{3}$$

The household specific preference parameter γ_{ik} captures the intensity of the taste for housing good, k. With this functional form, we can rewrite the first order condition as:

$$\frac{\gamma_{ik}}{x_{j*k}} = \frac{\delta\, \pi P\left(X_{j*}\right)}{\delta x_{jk}} \tag{4}$$

$$\gamma_{ik} = x_{j*,k} \frac{\delta\, \pi P\left(X_{j*}\right)}{\delta x_{jk}} \tag{5}$$

We readily obtained the measure $\frac{\delta\, \pi_t P(X_{j*})}{\delta x_{jk}}$ from the first stage estimation of the hedonic price function. We directly observe x_{j*k}, and therefore can calculate γ_{ik}, which is the household specific preference parameter for attribute k. Equation (4) provides the second stage hedonic estimation for the willingness to pay (the marginal rate of substitution) for housing good k. The preference parameter calculated in (5) for each household can be used to calculate willingness to pay for changes in amenity k. Households are characterized by their demographics, d. Using these attributes the preference parameter, γ_{ik}, can be decomposed into an average preference for k shared by all households, α_k, and household specific preferences α_{kd} based in part on observed demographics S_{id} and unobserved heterogeneity ω_{ik}:

$$\ln(\gamma_{ik}) = \alpha_k + \sum_d \alpha_{kd} S_{id} + \omega_{ik} \tag{6}$$

4. Econometric model

In the first step, we estimate the hedonic house price model using a Generalized Additive Model, with a gamma distribution and a logarithmic link function (Wood, 2006). The generalized additive function is a flexible and computationally efficient alternative to non-parametric or semi-parametric models such as local linear estimation. It allows the inclusion of a large number of covariates and utilizes splines to fit a flexible yet smooth functional form to the data. The data thus determine the shape of the function.[6]

$$\begin{aligned}\ln\left(P_j\right) = \alpha + f_1\left(G_j; S_1\right) + f_2\left(t_j; S_2\right) + f_3\left(x_j, y_j; S_3\right) + \sum f\left(X_j; Sj\right) \\ + \sum \left(Z_j\beta\right) Z_j\beta + \delta_h + u_j\end{aligned} \tag{7}$$

We distinguish between the variable, G, and other continuous housing characteristics, X and discrete housing characteristics Z. The f functions in (7) describe non-parametric smooth functions fitted using thin-plate splines where S describes the basis dimensionality, i.e., the flexibility allowed in fitting the function to the data.[7] Estimation of the smooth functions is based on generalized cross-validation. Please see Wood (2006) for a more technical description. All continuous variables that enter into the model are treated non-parametrically, this represented in (7) by the sum over function for housing characteristics, $\sum f(X_j; S_j)$.

It is an important assumption and requirement that G, the park variable, is exogenous in equation (7), and we argue that this is valid in our case. The parks in the study area have all been established a long time ago and most of them indeed date back to land uses decided upon before the

[3] This assumption is obviously strong though quite standard in the hedonic literature. As the current paper examines urban green space and the supply of green space is relatively stable over time in the area under study, we believe any resulting bias to be limited.

[4] Here π is set to 5%. For comparison, the Danish Central Bank used a measure of the user cost of housing of approximately 3% over the period.

[5] The utility function most cut the price-function from the right angle, in other words the second order condition must hold. The concavity of the utility function depends on the preference parameter γ_{ik} and the assumption of log utility.

[6] While this econometric approach is attractive, our results and identification does not hinge on this choice, as any flexible approach to estimating the price function can be used.

[7] The basis dimensionality was set to 5 for park variables while the other continues variables and the geographic smoothing is set automatically using Generalized Cross Validation criterion.

city developed around these areas. We explain further about this aspect below. Therefore, the decisions determining the locations of the parks included in the model are very plausibly exogenous to the households making transactions in our data set.

Nevertheless, in all hedonic studies omitted variable bias is a concern. The more recent literature addresses this concern with the use of, e.g., fixed effects as discussed in Kuminoff et al. (2010). Here we control for omitted spatially varying variables using spatial fixed effects to capture discrete changes at neighborhood borders as well as a flexible function of location to capture continuously varying omitted variables as suggested by von Graevenitz and Panduro (2015). In (7) the spatial fixed effect is represented by δ, covering h school districts. The functions $f_2(t_j; S_2)$ and $f_3(x_j, y_j; S_3)$ represent non-parametric controls for time (t) and space (x, y).

4.1. 2nd step: recovering preference parameters

In the second step the preference parameter of each household, γ_{ik}, for the k'th good is calculated based on the first order condition outlined in (5). Specifically, we use finite differencing to recover the change in the predictor associated with a small change in park access. This delivers a household specific estimate of the marginal willingness to pay, $MWTP_i$, for the good k, i.e. park proximity or density. The preference parameter estimate for this good, $\widehat{\gamma}_i$, is then recovered for each household by multiplying the park variable measure for the property j, G_{j^*} found in the observed housing choice with the asset return rate π and the marginal willingness to pay estimate.

$$\widehat{\gamma}_i = G_{j^*} \times \pi \times \partial P_j / \partial G_{j^*} \tag{8}$$

For (4) to hold, the good needs to be available in continuous amounts. If not, then the marginal rate of substitution and the marginal cost are not necessarily tangential to the purchased bundle. The implications would be that we cannot use (4) to recover the preference parameter for the good. Both park variables are continuous and if a household has chosen to buy the proximity or the density of parks we can use the condition in (8) to estimate the preference parameter, γ_{ik}. Due to the construction of our park availability variables - which we explain in details below - there may be apartments in the sample where the level of supply or access is zero. The preference parameters are unidentified for the households in these apartments, because the first order condition in (4) does not necessarily hold at or below the kink of the censored proximity distance variable.

4.2. 3rd step: decomposing preference heterogeneity

In the third step, the preference parameter is regressed on observed socioeconomic characteristics of households such as age, income, children and so forth, using OLS:

$$ln(\widehat{\gamma_{ik}}) = \alpha_k + \sum_{d}^{D} \alpha_{kd} S_{di} + \omega_{ik} \tag{9}$$

where α_k is an intercept that captures the average preference for the park measure G, S_{di} are D observed socioeconomic characteristics and α_{kd} is a vector of parameters describing the variation that can be explained by each observable characteristic. The parameter ω_{ki} captures the household's residual idiosyncratic taste heterogeneity for park proximity or park density.

5. Data

The data consists of 8880 apartments traded in central Copenhagen from the beginning of 2007 and to the end of 2011. The data include only arm length transactions. A small number of apartments traded for more than 2,421,240 EUR or less than 13,451 EUR were removed as they were considered to be either part of a different market (for very high-end properties) or reflect errors in the data, respectively. The data only included properties bought as residential apartments by private households. Besides sales price, date of transaction and type of sale, the data also include information on structural characteristics such as a number of rooms, size of the living area, outer wall construction material and so forth. The information was extracted from the Danish Registry of Buildings and Housing, which contains information on all dwellings in Denmark. The registry also contains information on the exact location of each property, which allowed us to calculate several proximity variables, e.g., to relevant spatial public goods, such as railway stations or shopping possibilities for each property. We did that using R (R Core Team, 2015) and ArcGIS 10.2.1 (ESRI, 2011, 2015). To ensure that the analysis did not suffer from an edge effect all spatial externalities less than 3 km outside of the border of the housing market were included in the calculation of spatial variables – see Fig. 1. The spatial data were supplied by the Danish Geodata Agency based on the kort10 database (The Danish Geodata Agency, 2011) and by the Danish Business Authority based on the CVR Registry (Danish Business Authority, 2011).

Individual-level socioeconomic data from Statistics Denmark were joined with each traded apartment using coordinates. Due to the sensitive nature of individual-level socioeconomic data, these were delivered spatially blurred using a raster mosaic of 100×100 m after which it was further refined and matched to individual properties by Geomatic A/S.[8] The socio-economic data applied in the analysis is on a household level, and their precision depends on the matching procedure applied by Geomatic.

6. Study area

The study area is located in the inner city area of the Danish capital, Copenhagen. The study area is one of the most attractive real estate markets for apartments in Denmark. The area is characterized by high sales prices of properties and high-income residents relative to the rest of Copenhagen. The study area was selected by spatial analysis of the residuals from a naïve hedonic house price model for the greater Copenhagen area (Lundhede et al., 2013). The residuals showed a clear pattern with areas of over- and under-prediction following distinct barriers in the urban landscape such as large roads, railway tracks, and large green spaces. The spatial distribution of the residuals indicated that the pricing of the study area was distinctly different from the rest of Copenhagen city. On this basis we consider the study area to be a single homogenous property market for apartments.

The inner city of Copenhagen includes a former industrial harbor and several recreational parks. Over the recent decades, the harbor has been transformed into a place for recreational activities. The larger recreational parks in Copenhagen originally served other purposes, such as defense systems, green pastures for livestock and owned by the University of Copenhagen, the Church or the Danish Monarchy. To some extent, the parks outline the historical city limit over different historical periods (see Fig. 1).

7. Park availability variables

We define a green space as a park only if the area has a high maintenance level with well-kept vegetation, and the area has to have footpaths making it possible to walk in the area and enjoy, e.g., small lakes, trees, lawns, flowers, and sports activities. This excludes, e.g., urban green areas around industrial buildings and infrastructure like railroads.

We apply two different measures: A simple proximity measure and a density measure. The two measures are illustrated in Fig. 2 and follow the main strategies applied in the literature on valuation of green space using

[8] Summary statistics of the data applied in this study can be found in Appendix A at the end of the paper.

Fig. 1. The outline of the inner city apartment market used as a study area. Green areas mark the recreational areas coded as parks in this study.

Fig. 2. The two measures for park supply - park density (left) Fig. 2a and proximity (right) Fig. 2b. The (red) spot indicates the property, and for the distance measure, the arrow indicates the beeline distance to the nearest green area (<1000 m). On the left, the circle indicates the 1000 m radius around the same property; a circle spanning slightly more than 314 ha.

the hedonic house price method. We ran a large number of different models, including a number of distance or density dummies, to investigate the empirical spatial extent of each measure in the data. We compared model performances, e.g., using information criteria and significance of parameter estimates, to obtain a set of good alternative specifications of both variables.

Using this method, we decided on a cut-off distance of 1000 m for the proximity measure. We use a flexible functional form for estimation allowing the impact of increasing proximity to a park to vary within 1000 m of the nearest park. A distance of 1000 m corresponds to about 12–15 min on foot, which in previous studies has been suggested as an upper limit for people's willingness to travel by foot to green space, before selecting other means of transport or destinations (Jensen and Koch, 2004; Schipperijn et al., 2010; Toftager et al., 2011).

The proximity measure is calculated from a Euclidian distance GIS calculation. The degree of proximity was calculated by $X_{prox} = C_{cut\text{-}off} - X_{dist}$ where X_{dist} describes Euclidian distance and C_{cutoff} is set to 1000 m. For apartments beyond this cut-off distance, the measure of proximity is set to zero. In this way, the proximity variable is easy to interpret, because positive preferences for a park will result in a positive parameter. The specification reflects that the value of the service declines with distance, and beyond some point will effectively be zero (Panduro and Thorsen, 2014). The measure is insensitive to how large the nearest area is as well as to areas beyond 1000 m.

Table 1
Summary statistics for park variables for the sample with non-zero consumption.

Variable	N	Mean	St. Dev	Min	Max
Density measured in ha within 1000 m	8487	20	19	0.002	73
Proximity in meter to park within 1000 m	8487	586	224	0.72	976

The density measure describes how many hectares of the park each apartment has access to within in a cut-off value, which we decided to set equal to 1000 m radius, be it any mixture of parks, e.g., several smaller parks or a single larger park. The density measure implies that the utility of park supply to the household depends on the total area of parks available within 1000 m of the property, but is insensitive to where in that radius the park is, as well as any parks further away.

The two park measures are simple, commonly used measures, and represent two distinctly different approaches to describe the relationship between property value and parks. They furthermore operate on different spatial scales with different density radius and cutoff values. The choice of spatial scale implies that a few households in our sample have not bought park availability and park proximity. As shown in Table 1, no apartment in the sample is closer than 24 m to a park (1000–976 m) and those apartments situated within 1000 m from a park have a mean proximity of 586 m (1000–414). The apartment with highest park density has about 73 ha of parks within a 1000-m radius, while the mean density is about 20 ha within a 1000 m radius.

Both park measures were calculated using Euclidian distance. However, networks distance measures were also considered. In a dense urban environment such as the study area, the route choice is not obvious, and it is not clear that a network distance measure will perform better than the simple Euclidean distance. In the early analysis, the network distance measures did not perform better regarding parameter efficiency or model fit. We, therefore, chose to apply the simpler Euclidian measures.

8. Results

8.1. The hedonic price function

We estimated three different hedonic price models, differing only in the park variables included. The smooth functions estimated for each of the park variables are shown in Fig. 3. The first model included only the density measure (Fig. 3a), the second model included only the proximity measure (Fig. 3b), and the third model included both measures (Fig. 3c and d). The implicit prices for park density can be seen to increase at different rates until 60 ha within 1000 m where after it levels off. This pattern can both be seen for the first model, that only contains the density measure and the combined model that contain both park measures. The implicit price for park proximity is seen to increase until 500 m near the park. The flexible non-parametric form then allows the implicit price to drop off somewhat and then it increases again to reach a maximum close by the park. We note that as the two variables are jointly included in the model (Fig. 3c and d), the park proximity variable is reduced in impact through the shape of the curves remains remarkably similar across models.

In Table 2, we show the distribution of the estimated percentage changes in the price associated with a small change in park access for each of the relevant park variables together with models statistics. The full models include more than 40 explanatory variables[9] and 8880 house sales. Here it suffices to say that the explanatory variables are stable across the three models and conform to expectations, e.g., increasing the number of rooms or the size of the living space is associated with higher prices and increasing the distance to the coastline is associated with lower prices. The pseudo-R-square is rather high (0.88), and the Log Likelihood value is similar across all models.[10]

The parameter for the density measurement is significant in both the models, where it appears. It can be interpreted as the implicit marginal price of an increase in park availability of one ha within 1000 m radius of the property. It corresponds to a price premium of 66.59 EUR per ha per year for the average apartment in the sample.[11] The proximity park measure captures the distance to the closest park within 1000 m. The mean estimate for the proximity specification suggests an additional property value of 1.06 EUR per meter per year for the average apartment. When incorporating both variables in one model, we found similar estimates 53.25 EUR per ha per year and 0.59 EUR per meter per year. In the left tail of the distribution, where impacts are insignificant, the implicit marginal prices are all negative, which is not surprising given the smooth curves depicted in Fig. 3a–d.

8.2. Sensitivity analysis

Our data sets allow us to control for all observable characteristics that may be correlated with the park variables. Furthermore, to evaluate whether our estimates are robust to unobserved spatial variables correlating with price and the variables of interest we followed the sensitivity analysis approach suggested by von Graevenitz and Panduro (2015). This approach consists of re-estimating the models with different specifications designed to capture omitted variables (e.g., fixed effects) to see how sensitive the estimates are to assumptions made about the spatial scale of such omitted variables. We have applied both a spatial additive model with two-dimensional splines of varying dimensionality to fit the spatial coordinates and a standard fixed effect model based on a variety of spatial entities. We found the parameters of the park availability measures to be robust across several increases in basis dimensionality for the spatial generalized additive model. Likewise, we found them to be stable across a number of spatial resolutions of the fixed effects specifications, including postal codes, parishes, school districts, infrastructure spatial segmentation and finally ownership organizations for apartment buildings. This supports our assumption that within-school district variation in park access is exogenous.

8.3. The 2nd step: recovering preference parameters

Preference parameters for the park measures were recovered for all three models. Due to the highly flexible non-parametric estimation, near zero and slightly negative implicit prices were found for the density measure at values approximately above 60 ha, while near zero and slightly negative implicit prices for the proximity measure were found between 500 and 750 m in proximity. The shaded areas in the smoothing plot represent 95% of expected sample prediction. Note that in these regions of negative implicit prices, the prediction area includes the value of zero, and these preference parameter estimates were therefore set to zero.

As can be seen from Table 3, a total of 8880 households bought an apartment in the period 2007–2011. In total 8032 households were found to have positive preference parameters for park density and 848 households had a negative preference parameter, for park density, which we set to zero. The mean preference parameter for those 8032 households from model 1 and 3 corresponds to a willingness to pay of 857 EUR/year and 774 EUR/year, respectively, for their present level of parks access relative to having no access to a park. A total of 8487 households had bought an apartment within 1000 m from a park while only 5274 and 4999 household were found to have a positive preference parameter

[9] The full model is included in Appendix B.

[10] It should be noted that due to the use of thin plate splines the models are not exactly nested.

[11] Mean transaction price in the sample is 325,712 EUR (2012).

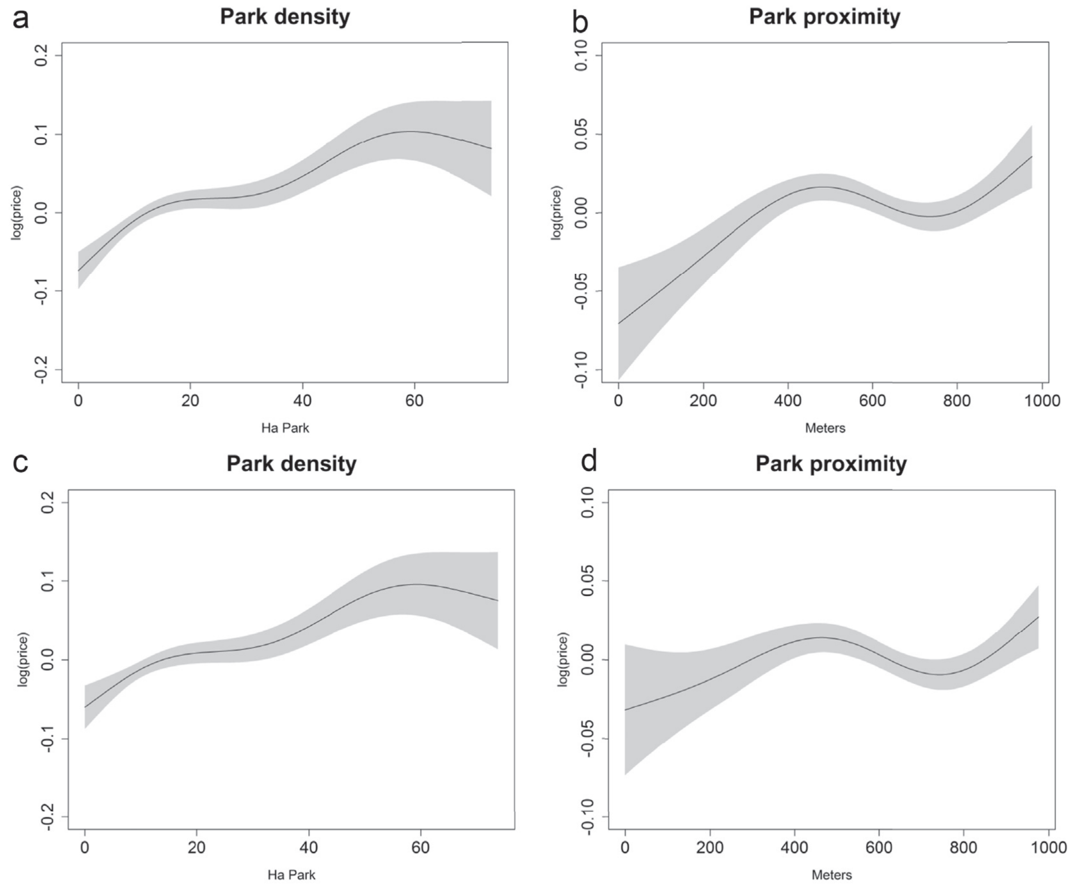

Fig. 3. The panels describe the non-parametric smooth functions estimated for the hedonic price function for the park measures for the three model specifications (cf. equation (7)). The shapes of the curves in Fig. 3 are highly informative as they show the implicit prices for the park attributes at different levels of the amenity. The first model (3a) included only the park density measure (number of ha within 1000 m), the second model (3b) included only the proximity measure (1000 m minus distance to nearest park within 1000 m), and the third model included both density and proximity measure (3c & 3d, respectively).

Table 2
The estimated implicit prices (EUR per year per ha or meters) obtained from the hedonic regression (equation (7)) for Park Density (ha within 1000 m) and Park proximity (1000 m minus distance to nearest park within 1000 m).

Model	Variable	25th percentile	50th percentile	Mean	75th percentile	Adj. R^2	Log Likelihood
1	Density (1 ha)	27.22	61.02	66.59	98.67	0.88	−107,555.74
2	Proximity (1 m)	−0.76	1.02	1.06	2.55	0.88	−107,560.46
3	Density (1 ha)	24.07	49.14	53.25	78.45	0.88	−107,543.97
3	Proximity (1 m)	−1.01	0.67	0.59	1.86	0.88	−107,543.97

Note: The models include school district fixed effects and a smooth function in the spatial coordinates to control for omitted neighborhood variables. See full models in appendix. N = 8880 transactions.

Table 3
Preference parameters estimated from equation (8) using each of the models from Table 2. Model 1 includes only density (hectares within 1000 m), Model 2 only proximity (1000 m minus distance to nearest park within 1000 m) and Model 3 including both. The parameter shows the households willingness to pay in EUR/year for their current park availability.

Model	Variable	N +	N -	Mean	Median	SD	Min	Max
1	Density	8032	848	857	470	1076	0.34	16,570.45
2	Proximity	5274	3606	1396	868	1437	0.17	17,142.72
3	Density	8032	848	774	373	1020	0.18	15,123.52
3	Proximity	4999	3881	1292	646	1489	0.55	16,863.35

Note: The results are presented in EUR/year across all households. Preference parameters are only recovered for the households who bought the good. N+ describes the number of households with a positive preference. Mean values are calculated including the households with preference parameters set to zero. N- describes the number of household with a preference parameter set to zero.

for proximity calculated from model 2 and model 3, respectively. For households located further away than 1000 m from a park, we cannot recover their preference parameter and conservatively set it to zero. Households located between 500 and 750 m in proximity to a park had a

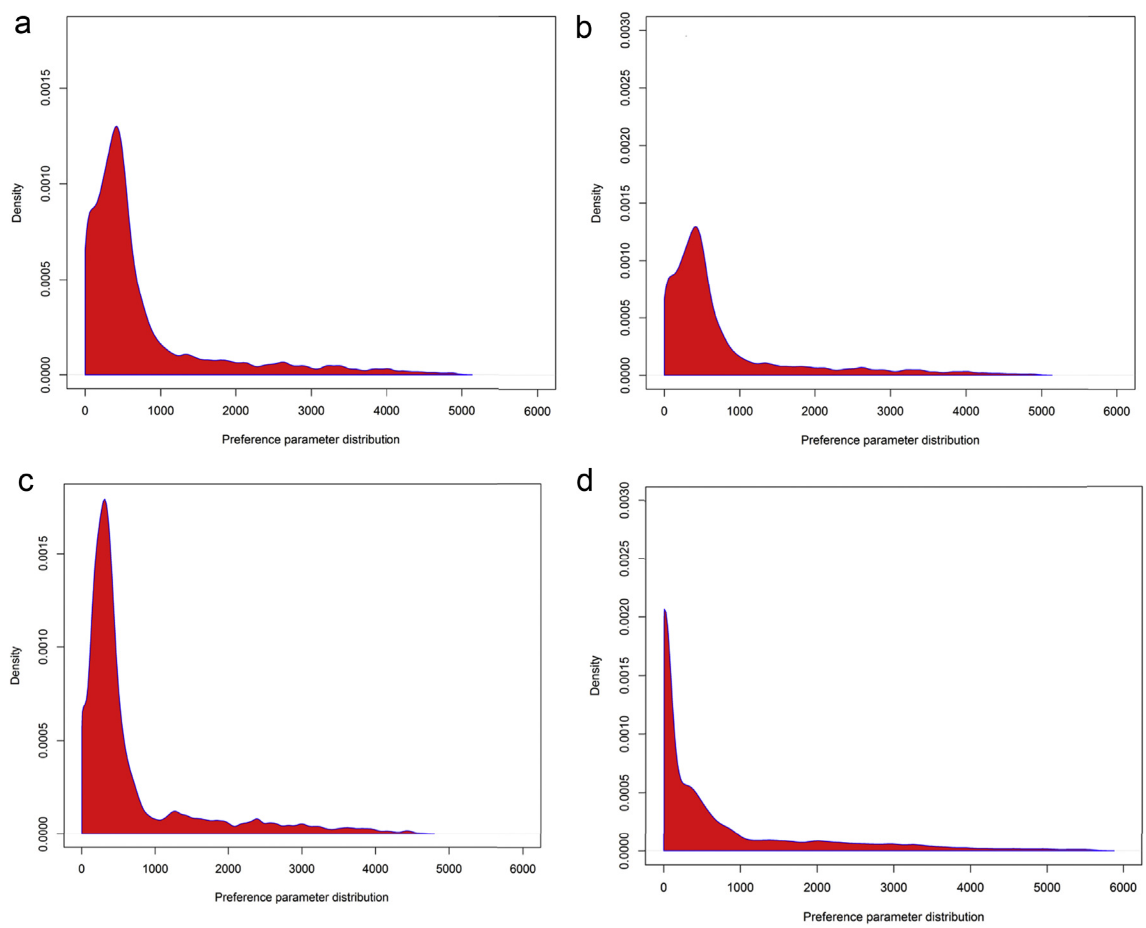

Fig. 4. The distribution of the preference parameter (willingness to pay) for park density (left) and park proximity (right) measured in EUR/year for the households current park availability, obtained using equation (8). Fig. 4a describes the distribution of the preference parameter for Model 1 including only density (ha of park within 1000 m). Fig. 4b describes the distribution of the preference parameter calculated from Model 2 including only proximity (1000 m minus distance to nearest park). Fig. 4c describes the distribution of the preference parameter for the density of park calculated from Model 3 including both measures. Fig. 4d describes the distribution of the preference parameter for park proximity calculated from Model 3, including both measures.

near zero preference parameter for marginally increasing proximity and were therefore set to zero.[12] We found a mean preference parameter for model 2 and 3 corresponding to a willingness to pay of 1396 EUR/year and 1292 EUR/year compared with a situation of with no park in the proximity.

Fig. 4 shows the distribution of the recovered preference parameters for the three different models. Some households have a willingness to pay far higher than the mean, resulting in a long right tail. In other words, the distributions reveal a large variation in taste across households where only a small proportion of the households have a very high willingness to pay. In particular for model 3, including both variables, the distribution shows that a high a number of households have a near zero preference parameter for proximity. The distribution for the preference parameter recovered using the density measure shows a wider range of values in both models. Most households have a preference parameter between 0 and a 1000 EUR/year.

8.4. *The 3rd step: decomposing preference variation*

We regressed the preference parameters obtained from Models 1, 2 and 3 on a number of sociodemographic variables, see Table 4. The preference parameter models in Table 4 explain about 10% of the variance of the calculated preference parameter. In consequence, 90% of the preference heterogeneity among households is attributable to idiosyncratic taste variation for park density and park proximity. The signs of the estimated parameters in the willingness to pay model largely conform to expectations.

The coefficients on the socio-economic variables are equal in size across the models estimated for the preference parameter for the proximity models and the density models. The preferences for park density resulted in a larger sample, which enabled a somewhat richer explanation of preference heterogeneity relative to the models based on the preference parameter for proximity only.

The preference intensity and willingness to pay for park availability increases with the age of the household heads. Younger households (defined by the oldest household member being under 30 years old) show a weaker taste for both park proximity and park density compared to households where the oldest household member is between 30 and 60. On the other hand, households, where the oldest member is above 60, show a stronger preference for density to parks.

Car owners appear to be less willing to pay for park density, which may reflect ease of reaching green recreational areas elsewhere. Car ownership also seems to affect preferences for park proximity negatively.

[12] The variation in MWTP across distances may seem puzzling. However, previous research by Abbott and Klaiber (2010) suggests that green space provides different amenities at different distances from a home. From e.g. a nice view for houses adjacent to green space, to recreative activities for homes somewhat further away. As negative MWTP estimates are inconsistent with the revealed preference for proximity to green space, we prefer the mechanical solution of setting negative MWTP estimates to zero. A technical solution to this problem would be to impose monotonicity in the estimation.

Table 4
Explaining heterogeneity in household preferences (willingness to pay in EUR/year for current availability) for park proximity and density. Measures are obtained from equation (8) based on a hedonic model (equation (7)) including both measures and regressed on socio-demographics, cf. equation (9). Results are reported for models with either proximity or density as the variable as well as for a model with both measures included combined.

	Dependent variable: Preference parameter for proximity		*Dependent variable:* Preference parameter for Density	
	Model 2: Single measure	Model 3: Combined measure	Model 1: Single measure	Model 3: Combined measure
Constant	5.811***	4.890***	5.086***	4.812***
	(0.192)	(0.225)	(0.124)	(0.118)
Income (1000 EUR)	0.018***	0.029***	0.020***	0.021***
	(0.003)	(0.003)	(0.002)	(0.002)
$Income^2$ (1000 EUR)	−0.0001***	−0.0001***	−0.00005***	−0.0001***
	(0.00002)	(0.00002)	(0.00001)	(0.00001)
Under age 30	−0.348***	−0.423***	−0.318***	−0.380***
	(0.034)	(0.040)	(0.025)	(0.024)
Above age 60	0.030	−0.150	0.274**	0.330***
	(0.170)	(0.197)	(0.131)	(0.125)
Min 5 years higher education	0.113***	0.018	0.100***	0.104***
	(0.036)	(0.043)	(0.027)	(0.026)
Top manager	−0.135***	−0.139***	−0.114***	−0.083**
	(0.045)	(0.054)	(0.034)	(0.032)
Car owner	−0.068	−0.157**	−0.259***	−0.315***
	(0.061)	(0.073)	(0.044)	(0.042)
Single	0.137	0.393**	0.232**	0.388***
	(0.164)	(0.191)	(0.102)	(0.098)
Children	0.479***	0.839***	0.456***	0.592***
	(0.163)	(0.190)	(0.100)	(0.095)
Single parent	−0.404**	−0.677***	−0.363***	−0.511***
	(0.167)	(0.194)	(0.103)	(0.098)
Single above age 60	−0.717***	−0.865***	−0.443***	−0.634***
	(0.199)	(0.232)	(0.143)	(0.137)
Observations	5272	4993	8030	8025
R^2	0.089	0.111	0.106	0.128
Adjusted R^2	0.087	0.109	0.104	0.127
Residual Std. Error	1.095	1.258	1.007	0.961
F Statistic	46.616***	56.704***	86.024***	107.037***

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

However, the parameter estimate is only significant for one of the proximity models.

Families with children are inclined to buy more park density, though the effect is almost exactly canceled out if it is a single parent family. The parameter estimate for children based on the proximity models are both insignificant.

The preferences of a single person household are interesting as this is a fast-growing household type in many western urbanized regions, including Copenhagen. Our analyses reveal that being single is associated with an increase in preference intensity for park availability, except for those above 60, who had much weaker preferences as evidenced by the negative and highly significant coefficient. We find that the higher the educational attainment of the household heads, the greater the preference for park density. For households, with minimum one member in a top management position, we find lower preferences for both park density and park proximity.

From the lowest to the highest income group in the sample the preference intensity for park density increase by more than 150%. Education and work position tend to correlate with income, as do also car ownership and age. Having corrected for these variables, our analysis reveals that preferences also depend on income directly. This measure of affluence was found to best capture the preference parameter using a quadratic function using the PanJen functional form ranking (Jensen and Panduro, 2018). The implication is that the preference intensity for park density and proximity will increase at a decreasing rate almost leveling off at high-income levels at incomes above 150,000 EUR per year for the household member with the highest income. A similar pattern of increasing preference intensity at a decreasing rate is found for the park proximity models.

9. Policy evaluation

The model estimates of the willingness to pay function above provide the possibility to assess the welfare effects of a non-marginal change in the availability of the park good. Based on the preference parameter for parks, the willingness to pay for a change in park consumption can be calculated as follows $\widehat{\gamma}_{Gi}(\log(G_i^1) - \log(G_i^0))$, where current proximity or density of parks is represented by G_i^0 and G_i^1 represents the scenario of change, e.g. a new park established or alternatively an existing park cancelled and developed for other purposes. A scenario like the latter, where a park is converted to other land-use purposes e.g. parking lots, commercial activities or apartment blocks is fictional, yet not implausible in a dense city like Copenhagen. Like any other major city in a western European country, the pressure to convert remaining open urban spaces to other types of land-uses is high in Copenhagen given the relatively high land rent.

To exemplify the impact of a policy intervention where an entire park is converted to something else we calculate the welfare loss of removing the romantic style and more than 150 years old Horticultural Garden (Landbohøjskolens Have) at University of Copenhagen. The Horticultural Garden is mapped in Fig. 5 along with the catchment areas of the proximity measure and density measure. Note that The Horticultural Garden is located on the Frederiksberg Campus at the University of Copenhagen resulting in only few apartments located adjacent to the park. An inspection of the other parks in Copenhagen revealed that it is common to have non-residential buildings (public buildings, business, etc.) located close by the parks. The Horticultural Garden is similar to other parks in Copenhagen regarding accessibility measured in proximity and availability measured in density. However, the Horticultural Garden is considered to be a particularly well-maintained and beautiful space and the estimated welfare effects calculated here should be considered appropriate for an average park in the sample area rather than this particular park. We assume that whatever the area is developed into, the new land use does not affect the values of the apartments in focus, e.g., it may be further residential building blocks. In the calculation, we account for a possible substitution effect.

We calculated the annual welfare loss for a scenario without the Horticultural Garden for both the proximity measure and the density measure. We based our approach on the first stage hedonic regression assuming that the homes transacted in the market are representative of what the market has to offer and that people moving in have the same preferences as the people moving out. Thus the coefficients of the hedonic function, which describes the market equilibrium, were used to predict transaction prices for affected properties. Based on these predicted transaction prices, we calculated preference parameters for the households according to (5) and used these predicted preferences to calculate willingness to pay for the changes resulting from removing the Horticultural Garden. Preference parameters calculated to be less than zero were set to zero.

The results of the calculation are presented in Table 5. The aggregated annual welfare loss was estimated to 3.72 mill. EUR/year for Model 1 including only the proximity measure, whereas the welfare loss was 3.46 mill. EUR/year for Model 2 including only the density measure. If both measures were accounted for, using Model 3, the annual welfare loss was estimated to 7.08 mill. EUR/year. The difference between the welfare economic calculations is a result of both the spatial extent of each measure, possible substitutions, the size of the change and its distributional implications. In our case, it means that about five times as many apartments would be affected when using the density measure compared to

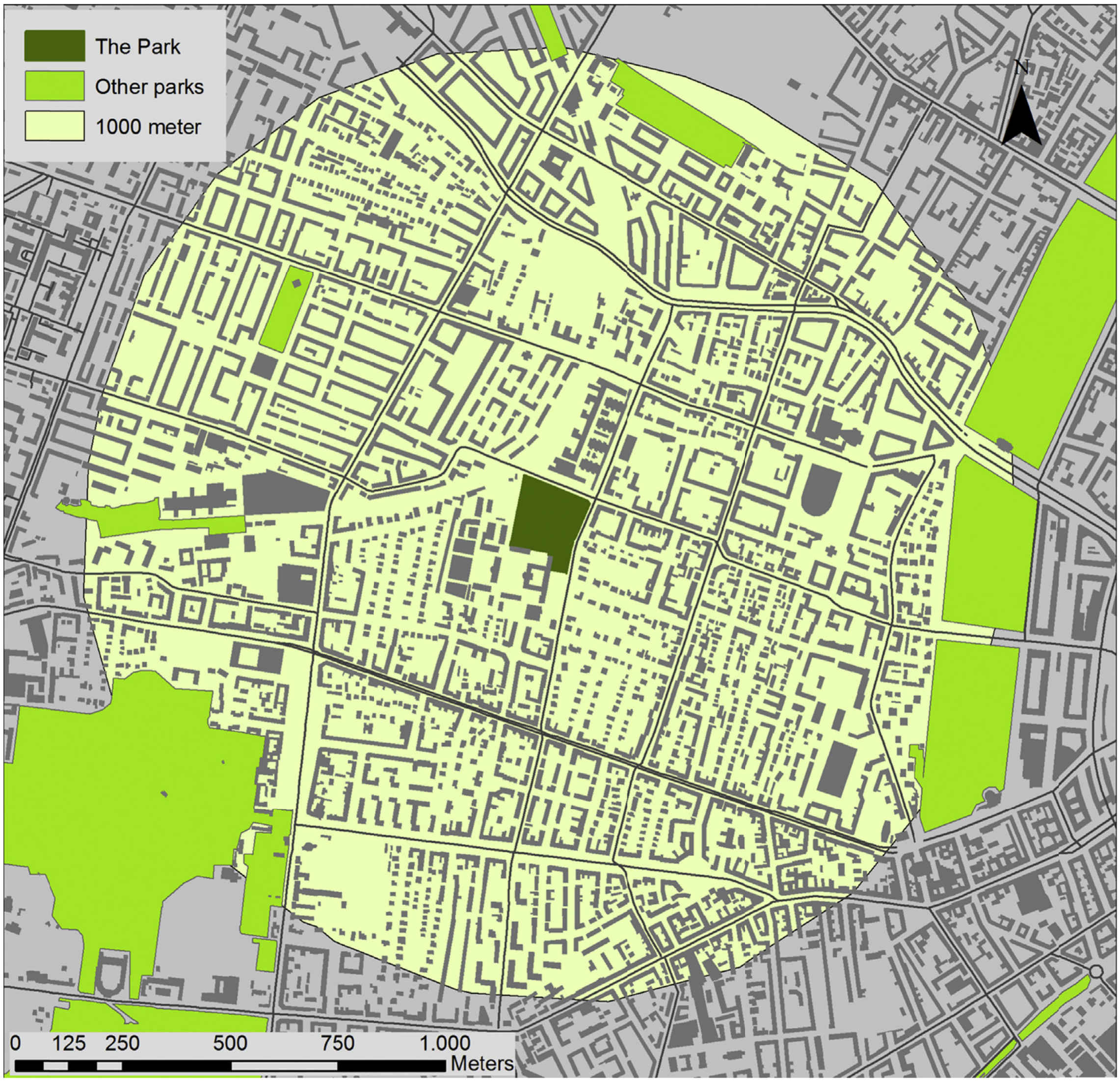

Fig. 5. The proximity and density catchment area around the Horticultural Garden of University of Copenhagen.

Table 5
The distribution of welfare changes from removing the Horticultural Garden, as experienced by households in the area (see Fig. 5) and measured in EUR/year. Estimates are reported for Model 1 including only a density measure (ha within 1000 m), Model 2 including only a proximity measure (1000 m – distance to nearest park) and Model 3 including both measures.

	Min	1st Qu.	Median	Mean	3rd. Qu	max	N	Aggregated welfare change
Model 1 Density	−806.58	−144	−92	−90	0	0	38,300	−3,458,253
Model 2 Proximity	−18,929	−345	0	−535	0	0	6960	−3,726,173
Model 3 Combined	−20,776	−145	−84	−184	0	0	38,300	−7,079,360

the proximity measure. The effect of the difference in distributional impact can be seen on the mean willingness to pay between the two measures, where the individual household's welfare loss is many times higher for the proximity measure compared to the density measure.

The amount of park per household varies substantially across the specifications: For the density measure, the loss of the Horticultural Garden leads to a median percentage change of 5.7 for the affected households (see Table 6). For the proximity measure, the change for each household is much larger with a mean loss of 30%.

The non-marginal effect on individual households can be rather large depending on location and choice of measurement. However, the shock to the Copenhagen apartment market is most likely limited. The change affects less than 7000 homes, which is a very small part of the Copenhagen housing stock. In this perspective, one might argue that the hypothetical removal of the Horticultural Garden could be a non-marginal localized event in the housing market following the definition of Bartik (1988), and is unlikely to lead to, e.g., sorting effects in a short

Table 6
The distribution of the relative change in the two park measures ‘Proximity’ and ‘Density’ from removing the Horticultural Garden for the households in the area (see Fig. 5).

	Max	3rd Qu.	Median	Mean	1st. Qu	Min	N
Proximity	81	44	30	31	16	0	6960
Density	25.3	6.9	5.7	7.1	3.9	2.8	38,300

to medium timespan.

The different results of the three policy evaluations stress the importance of how the relationship between parks and property price is constructed in the hedonic model, as it clearly affects the estimated welfare economic impact, and distribution of effects, and thus the potential policy implications. The aggregated welfare loss and the burden dispersed across households differ substantially between the three hedonic specifications. Using the proximity measure approximately 6960 households share the loss, with an average lose 535 EUR/year. In the density case, a smaller loss of 90 EUR/year is shared by five times as many households. While in the case where the proximity and density measurements are combined the average loss equates to 184 EUR/year.

10. Discussion

Our main aim of this study is to enhance our insight into the value of urban parks applying the Bajari and Benkard (2005) framework to recover and analyze preference variation for urban parks across households. Our second aim was to illustrate why it is important for policy conclusions, that researchers pay attention to the way variables measuring the urban park attribute are specified and modeled.

10.1. The first stage hedonic price function

Many studies have presented first stage hedonic price functions using various measures of park availability for urban residents. In the present study, we applied two of the most prominent measures each in two separate models and combined in a joint model. These are park proximity, measured as distance to nearest park and censored at 1000 m, and park density, which measures the area of parks available within a radius, here 1000 m. Similar measures are used extensively in the literature (e.g., Lake et al., 2000; Mansfield et al., 2005; Kong et al., 2007; Cho et al., 2009; Jiao and Liu, 2010). We find that both the density and the proximity measures have significant explanatory power both separate and combined, as did also Kong et al. (2007). The estimated non-parametric relationship between price and the park measures recover a meaningful functional form. The proximity measure depicts a relationship where the marginal willingness to pay increase until 500-m proximity, then levels off somewhat and increases again at about 200 m. Our functional form for accessibility is more flexible in some ways than those used by, e.g., Lake et al. (2000) and Mansfield et al. (2005). The marginal willingness to pay for park density increases up to the point of about 60 ha after which it levels off. This suggests the existence of a saturation point where the amount of park in an area does not add additional value to households.

We find that both the proximity and the density measure can be included within the same model, suggesting they capture different aspects of urban park availability. To exclude one or the other park measure in an analysis would lead to a situation where not all attributes are accounted for. We initially estimated the models using a parametric approach where we found that both measures in the same model lead to insignificant estimates of the park proximity. This finding underlines the superiority of the non-parametric approach adopted in the paper. The more general model is to be preferred as it captures more dimensions of the amenity.

10.2. The second stage: recovering preference parameters

There are very few second stage hedonic price studies in the environmental economics literature altogether, and in fact, only one which has addressed the demand for urban parks, namely Poudyal et al. (2009). Part of the explanation for this is likely the challenges of setting up a valid identification strategy. Here, we introduce to the field a transparent identification strategy based on functional form assumptions, which was suggested and applied by Bajari and Benkard (2005) and has been later applied by Bajari and Kahn (2005) and von Graevenitz (2018). While the functional form restriction may be a strong, and potentially inaccurate, restriction, it may also be a (good specific) local approximation for the unknown true form. We return to this below.

The results of our second stage estimation show that parks in the inner city of Copenhagen provide a considerable flow of value to the residents. Households in Copenhagen are willing to pay a considerable amount for parks, be it either proximity or high density of parks near their homes.

10.3. Decomposing preference heterogeneity

Any policy change has distributional consequences, and drivers like demographic changes may imply new demands and policies. Therefore, it is of interest to policymakers and urban designers to understand patterns of preference heterogeneity. We find that the socio-economic background of the households can explain the preference variation to some extent. In particular, the patterns relating to families with or without children and the issue of single person households are interesting. The growing number of single households is an urban trend, which our results suggest could enhance the demand for urban park availability.

10.4. Policy evaluation and the choice of park availability measure

Our case study demonstrates that policy evaluation outcomes may hinge crucially on proper model design. Removing the park in the core of Copenhagen results in an aggregated total welfare loss for the neighboring households between 3.5 and 7 mill EUR annually, and the latter estimate results from a model accounting for both measures of availability. Approximately 7000 households share the aggregated loss using proximity and only those household within a distance of 1000 m are affected whereas more than 38,000 households share the aggregated loss using the density variable. Clearly, for both measures, the people living closest to the park stand to lose the most from potential park closure. Both measures capture the households situated close to the park, but where the model using the proximity measure predicts that it is this group who will suffer the major part of the loss, the model using the density measure also includes smaller losses to a wider group of people including those living further away.

On a strategic level, the two park measures could result in different policy strategies being developed. Focusing on proximity measures could lead to a strategy of many smaller parks, as aggregate area is ignored. The opposite could be true if the density measurement is the only focus, as proximity is ignored. The key goal would be to ensure as high a level of park availability as measured by the density measure, for the lowest cost. In this paper, we find that the proximity measure and the density measure do not compete but are complementary in the description of the marginal willingness to pay for urban parks. Therefore, the better strategy to would be to strike a balance between proximity and density in the preservation and development of parks in an urban area.

10.5. Caveats

There are specific and general caveats in the approach and results presented in this paper worth mentioning. First, we note that our dataset describing sociodemographic variables for all households are related to the residents in the last year of our cross section, 2011. Using coordinates of dwellings, these were joined with all sales in the period 2007–2011. We essentially assume that the new residents are moving to the area in the period 2007–2011 have the same observed socioeconomic characteristics as those who are already living in the area – or at least that the socio-demographic mean parameters of the 100×100 m fitted mean estimates were constant over the period. This might not be the case, but on the other hand, we have no reason to believe that the composition of people has changed substantially during the relatively short period.

A second general caveat of the hedonic method, which is also true for our application here, is, that when using the hedonic method for a policy change like the one evaluated, we only include the welfare effects of people living in the neighborhood. People further away, including the more than 1500 university employees and 4000 students on that part of the campus, who visit the Horticultural Garden or who have other bonds to the garden may also experience welfare effects. These are not accounted for in any hedonic analysis.

We also note that the welfare economic loss here does not include attention to property taxes. As noted by Anthon et al. (2005) and Zhou et al. (2013), property owners in Denmark pay property taxes based on the market value of their property. This imply that any change in value – upward or downward – also affects expected tax payments. Housing market prices reflects this. Thus, our estimated loss here is a conservative measure of the true loss as it only captures the net loss for households and not the effect of reduced property taxes.

The Bajari and Benkard (2005) approach is subject to criticism. The functional form restriction may be a strong and potentially inaccurate restriction. However, we view the chosen functional form as a (reasonable specific) local approximation for the unknown true form. This identification strategy does not require restrictions on preference heterogeneity nor does it require assumptions about sorting behavior. We have chosen a simple functional form due to its useful properties and avoided assumptions on preference heterogeneity. It represents a local approximation to the unknown true functional form. Strong assumptions concerning the unknown distribution of preference heterogeneity are common elsewhere in the consumption literature, e.g., in the Random Utility Model framework (McFadden, 1973). In our study, where preference heterogeneity is in focus, an approach requiring restrictions on preferences along this dimension would not be suitable.

11. Concluding remarks

The value of urban parks and green space for urban residents continuously attracts the interest of many types of research, including economics. A fairly large number of studies have estimated hedonic price functions for parks, other green areas, trees and similar goods and it is likely that this literature of applied environmental economics will continue to grow and increase the evidence for the obvious values of urban parks and green spaces.

However, there is an unfortunate shortage of studies addressing the estimation of demand for urban parks and green spaces; that is succeeding in estimating the so-called second stage of the hedonic model framework.

In this study, we obtain new insights into the preferences for and value of urban parks by applying a framework suggested by Bajari and Benkard (2005), where identification of preferences rely on functional form restrictions on the utility function. Second, we demonstrated how urban parks provide non-negligible flows of value and that preferences for park availability vary with socio-demographics in ways that may have interesting policy implications. Thirdly, using two standard measures of park availability, we demonstrated just how critical a proper choice of such measures is for the policy evaluation outcome.

Acknowledgment

This paper benefited from the project ”Benefits from investing in urban life and urban qualities.” funded in a collaboration between the municipalities of Aarhus, Albertslund, Brøndby, Frederiksberg, Gladsaxe, Glostrup, Herlev, Hvidovre, Ishøj, Københavns, Lyngby-Taarbæk, Rødovre, Skanderborg, and Vallensbæk and the Capital Region of Denmark, the Ministry of Environment and Food, the developers Kildebjerg Ry A/S, By & Havn I/S and the University of Copenhagen. Thorsen and Lundhede further acknowledge funding from the Danish National Research Foundation (DNRF No. 96) for the Center for Macroecology, Evolution, and Climate.

Appendix A. Descriptive statistics and variable explanation

Appendix A.1

The Appendix contains a description of the variables used in the hedonic price function and in the preference heterogeneity analysis.

Table A.1
Description of variables in the hedonic price function.

Name of variable	Description
Price	The transaction price of the property in EUR.
Time	The analysis period measured in days starting from January 1st, 2007 to December 31st, 2011.
x	The x coordinate measured in UTM 32 North WGS 1984
y	The y coordinate measured in UTM 32 North WGS 1984
Size	The size of the living area in square meters.
Room	The number of rooms in the apartment.
Built after 2000	Dummy variable that describes whether the apartment building was built after 2000. 1 corresponds to being built after 2000 and 0 corresponds to being built before 2000.
Built between 1980 and 1999	Dummy variable that describes whether the apartment building was built between 1980 and 1999. 1 corresponds to being built between 1975 and 1999 and 0 corresponds to not being built between 1980 and 1999.
Built between 1948 and 1979	Dummy variable that describes whether the apartment building was built between 1948 and 1979. 1 corresponds to being built between 1948 and 1979 and 0 corresponds to not being built between 1948 and 1979.
Built between 1947 and 1910	Dummy variable that describes whether the apartment building was built between 1910 and 1947. 1 corresponds to being built between 1910 and 1947 and 0 corresponds to not being built between 1910 and 1947.
Built between 1909 and 1875	Dummy variable that describes whether the apartment building was built between 1875 and 1909. 1 corresponds to being built between 1875 and 1909 and 0 corresponds to not being built between 1875 and 1909.
Tile roof	Dummy variable that describes whether the roof is made of tile. 1 corresponds to being built of tile and 0 corresponds to not made of tile.
Cement roof	Dummy variable that describes whether the roof is made of cement. 1 corresponds to being built of cement and 0 corresponds to not made of cement.
Felt roof	Dummy variable that describes whether the roof is a felt roof. 1 corresponds to being a felt roof and 0 corresponds to not being a felt roof.
Fiber board roof	Dummy variable that describes whether the roof is made of fiberboard. 1 corresponds to being made of fiber board and 0 corresponds to not made of fiber board.
Flat Fiber board roof	Dummy variable that describes whether the roof is a flat fiber board roof. 1 corresponds to being a flat fiber board and 0 corresponds to not being a flat fiber board.
Renovation 1980s	Dummy variable that describes whether the apartment has undergone major renovation during the 1980s. 1 corresponds to major renovations and 0 corresponds to no major.
Renovation 1990s	Dummy variable that describes whether the apartment has undergone major renovation during the 1990s. 1 corresponds to major renovations 0 corresponds to no major renovation.

(*continued on next column*)

Table A.1 (*continued*)

Name of variable	Description
Renovation 2000s	Dummy variable that describes whether the apartment has undergone major renovation during the 2000s before the apartment is sold. 1 corresponds to major renovations and 0 corresponds to no major renovation.
Number of buildings	The number of buildings in the apartment complex.
Number of units	The number of apartment units in the apartment complex.
Large Road	Proximity to the nearest large road described on a scale from 0 to 200 m where 0 corresponds to a distance of 200 m and 200 corresponds to being located directly on the large road.
Railway track	Proximity to the nearest railway track described on a scale from 0 to 200 m where 0 corresponds to a distance of 200 m and 200 corresponds to being located on the railway track.
Traffic noise >75 dB	Dummy variable that describes whether the apartment is located in an area where the average traffic during the day is above 75 dB. 1 corresponds to being located in a traffic noise zone above 75 dB and 0 corresponds to not to being located in a traffic noise zone above 75 dB.
Traffic noise 70–74 dB	Dummy variable that describes whether the apartment is located in an area where the average traffic during the day is between 70 and 74 dB. 1 corresponds to being located in a traffic noise zone between 70 and 74 dB and 0 corresponds to not to being located in a traffic noise zone between 70 and 74 dB
Traffic noise 65–69 dB	Dummy variable that describes whether the apartment is located in an area where the average traffic during the day is above 75 dB. 1 corresponds to being located in a traffic noise zone above 75 dB and 0 corresponds to not to being located in a traffic noise zone above 75 dB.
Traffic noise 60–64 dB	Dummy variable that describes whether the apartment is located in an area where the average traffic during the day is above 75 dB. 1 corresponds to being located in a traffic noise zone above 75 dB and 0 corresponds to not to being located in a traffic noise zone above 75 dB.
Coastline	Proximity to the nearest coastline described on a scale from 0 to 300 m where 0 corresponds to a distance of 300 m and 300 corresponds to being located directly on the coastline.
Number of shopping possibilities	Number of shopping possibilities within a 1000 m walking radius
Diversity of shopping possibility	The diversity of shopping possibilities within a 1000 m walking radius
Number of rental apartments	The number of rental apartments within a 1000 m walking radius
Number of residents	The number of residents within a 1000 m walking radius
Park density	The number of hectares within a 1000 m beeline distance
Park proximity	Proximity to the nearest park described on a scale from 0 to 400 m where 0 corresponds to being at a distance of 400 m and 400 corresponds to being located on the border of the park

Table A.2
Summary statistics of the variables in the apartment model.

Variable	Mean	St. Dev.	Min	Max
Size	91.67117	35.71755	32	401
Room	3.03153	1.14267	1	10
Built after 2000	0.15827	0.36501	0	1
Built between 1980 and 1999	0.02402	0.15312	0	1
Built between 1948 and 1979	0.18679	0.38976	0	1
Built between 1947 and 1910	0.21242	0.40904	0	1
Built between 1909 and 1875	0.35363	0.47812	0	1
Tile roof	0.29809	0.45744	0	1
Cement roof	0.01469	0.12032	0	1
Felt roof	0.31954	0.46632	0	1
Fiber board roof	0.14293	0.35002	0	1
Flat Fiber board roof	0.14615	0.35328	0	1
Bathroom	1.026	0.23945	0	3
Renovation 1980s	0.01823	0.13378	0	1
Renovation 1990s	0.03463	0.18286	0	1
Renovation 2000s	0.03549	0.18503	0	1
Number of buildings	1.79583	10.10624	1	242
Number of units	44.64065	50.92139	1	253
Large Road	34.206	58.095	0	190.210
Railway track	12.262	36.154	0	18.639
Park proximity	1.377	1.474	0	4.760
Park density	19.583	19.00.5	0	73.844
Time	728.375	43.751.250	0	1.460
Traffic noise >75 dB	0.00397	0.06287	0	1
Traffic noise 70–74 dB	0.04643	0.21042	0	1
Traffic noise 65–69 dB	0.09457	0.29264	0	1
Traffic noise 60–64 dB	0.21231	0.40896	0	1
Coast line	4.184.109	8.474.363	0	297.317
Number of shopping possibilities	56.698960	38.206080	10	2209
Diversity of shopping possibility	47.423	1.056726	7	57
Number of rental apartments	968.499	70.018290	0	2613.345
Number of residents	19,146.630	9858.619	0	41,543

Note: N = 8880.

Table A.3
Summary statistics of the fixed effect school districts in the model.

Fixed effect				
School district	Mean	St. Dev.	Min	Max
Amager Fælled Skole	0.02809	0.16525	0	1
Christianshavns Skole	0.04504	0.20739	0	1
Den Classenske Legatskole	0.03817	0.19162	0	1
Gasværksvejens Skole	0.00804	0.08932	0	1
Guldberg Skole	0.03238	0.17702	0	1
Heibergskolen	0.00836	0.09107	0	1
Kildevældsskolen	0.04171	0.19994	0	1
Klostervængets Skole	0.01222	0.10989	0	1
Langelinieskolen	0.04986	0.21767	0	1
Lindevangskolen	0.05061	0.21921	0	1
Lundehusskolen	0.01330	0.11455	0	1
Ny Hollænderskolen	0.05672	0.23133	0	1
Nyboder Skole	0.02616	0.15963	0	1
Oehlenschlægersgades Skole	0.02295	0.14974	0	1
Randersgades Skole	0.02766	0.16402	0	1
Skole ved Søerne	0.02241	0.14802	0	1
Skolen i Sydhavnen	0.05243	0.22291	0	1
Skolen på Duevej	0.04568	0.20880	0	1
Skolen på Islands Brygge	0.04589	0.20926	0	1
Skolen på la Cours Vej	0.03067	0.17242	0	1
Skolen på Nyelandsvej	0.04579	0.20903	0	1
Skolen ved Bulowsvej	0.04954	0.21700	0	1
Sortedamskolen	0.01072	0.10300	0	1
Strandvejsskolen	0.03163	0.17503	0	1
Sølvgades Skole	0.02992	0.17037	0	1
Søndermarkskolen	0.02606	0.15931	0	1
Tove Ditlevsens Skole	0.02209	0.14698	0	1
Valby Skole	0.00558	0.07447	0	1
Vesterbro Ny Skole	0.02262	0.14871	0	1
Vibenshus Skole	0.05662	0.23112	0	1
Øster Farimagsgades Skole	0.01909	0.13684	0	1
Ålholm Skole	0.00043	0.02071	0	1

Note: N = 8880.

Table A.4
Variable description of the socio-economic variables used in the willingness to pay function.

Name of variable	Description
Income (in 1000 EUR)	Measure the income of the highest earning person in the household measured in steps of 1000 EUR.
Min 5 years higher education	The adults in the household have minimum 5 years of education. The variable is constructed as a dummy variable which equals 1 when they have minimum 5 years of education and 0 Otherwise.
Top manager	The occupation of a member of the household is top manager. The variable is constructed as a dummy variable where 1 equals having a top manager in the household and 0 equals not having a top manager in the household.
Car owner	The household own a car. The variable is constructed as a dummy variable where 1 equals having a car and 0 equals having no car.
Single	The household have only one adult. The variable is constructed as a dummy variable where 1 equals having only one adult in the household and 0 equals having more than one adult in the household.
Children	The household have one or more children. The variable is constructed as a dummy variable where 1 equals having one or more children in the household and 0 equals having no children in the household.
Under age 30a)	The oldest member of the household is under 30 years of age. The variable is constructed as a dummy variable where 1 equals having no adults above 30 years age in the household and 0 equals having at least one adult over 30 years of age in the household.
Above age 60b)	The oldest member of the household is above 60 years of age. The variable is constructed as a dummy variable where 1 equals having at least one adult above 60 years age in the household and 0 equals having zero adults over 60 years of age in the household.

Table A.5
Summary statistics of the socio-economic variables used in willingness to pay function.

Variable	Mean	St. Dev.	Min	Max
Income (in 1.000 EUR)	57.77367	22.52489	17.86070	199.42330
Min 5 years higher education	0.51212	0.49988	0	1
Top manager	0.29466	0.45591	0	1
Car owner	0.18186	0.38575	0	1
Single	0.76968	0.42106	0	1
Children	0.70963	0.45396	0	1
Under age 30[a]	0.36414	0.48121	0	1
Above age 60[b]	0.04321	0.20335	0	1

Note: N = 8880.

[a] For 481 households the age of the oldest member of the household is only known to be less than 50 and for 268 households the age is only known to be less than 60. We assume the age to be minimum 30.

[b] For 189 households the age of the oldest member of the household is only known to be above 40 and we assume the age to be less than 61.

Appendix B. First stage model results

First stage - results			
	log (house price)		
	Density	Proximity	Combined
Tile roof	−0.00867	−0.01649**	−0.01082
	(0.00831)	(0.00832)	(0.00833)
Cement roof	−0.04616***	−0.05482***	−0.04681***
	(0.01680)	(0.01680)	(0.01680)
Fiber board roof	−0.01279	−0.01932**	−0.01394*
	(0.00815)	(0.00815)	(0.00816)
Board roof	−0.01172	−0.01874**	−0.01295
	(0.00860)	(0.00858)	(0.00864)
Flat roof	−0.03521***	−0.04036***	−0.03666***
	(0.00882)	(0.00885)	(0.00884)
Bathrooms	0.07077***	0.06834***	0.06992***
	(0.00779)	(0.00779)	(0.00779)
Renovated in 1980s	0.00915	0.00834	0.01063
	(0.01308)	(0.01309)	(0.01308)
Renovated in 1990s	−0.03508***	−0.03809***	−0.03537***
	(0.00956)	(0.00955)	(0.00956)
Renovated in 2000s	0.07228***	0.07543***	0.07497***
	(0.00911)	(0.00914)	(0.00914)
Noise level 1	−0.03737	−0.03964	−0.03785
	(0.02742)	(0.02741)	(0.02737)
Noise level 2	−0.04040***	−0.04146***	−0.04018***
	(0.00832)	(0.00833)	(0.00833)
Noise level 3	−0.02381***	−0.02355***	−0.02416***
	(0.00606)	(0.00609)	(0.00608)
Noise level 4	−0.01331***	−0.01433***	−0.01362***
	(0.00418)	(0.00419)	(0.00419)
Square meters	df = 7.5***	df = 8.2***	df = 8.5***
Number of floors	df = 6.9***	df = 7.7***	df = 7.7***
Age of building	df = 8.6***	df = 9.0***	df = 9.0***
Number of rooms	df = 4.7***	df = 5.7***	df = 5.7***
Number of buildings in the housing unit	df = 1.0***	df = 1.0***	df = 1.0***
Number of apartments in the building	df = 8.5***	df = 8.9***	df = 8.9***
Proximity to big road (censored at 200 m)	df = 5.8***	df = 6.2***	df = 6.5***
Proximity to railway tracks (censored at 200 m)	df = 8.9***	df = 9.0***	df = 8.9***
Proximity coastline (censored at 300 m)	df = 5.2***	df = 5.4***	df = 5.4***
Number of services within 1000 m	df = 8.1*	df = 7.9*	df = 8.0
Diversity of services within 1000 m	df = 8.9***	df = 9.0***	df = 9.0***
Number of children in nearest daycare center	df = 8.8***	df = 8.9***	df = 8.7***
Number of rental apartments within 1000 m	df = 8.9*	df = 8.8***	df = 9.0***
Number of residence within 1000 m	df = 8.2***	df = 9.0***	df = 8.6*
Numeric vector describing time of sale	df = 8.9***	df = 8.9***	df = 8.9***
Geografical coordinates (x,y)	df = 28***	df = 27.8***	df = 28.1***
Park density	df = 4.0***		df = 3.6***
Park proximity		df = 3.7***	df = 3.9***
Constant	12.49922***	12.50662***	12.49852***
	(0.02520)	(0.02522)	(0.02546)
Adjusted R^2	0.87971	0.87935	0.87999
Log Likelihood	−107,736.10000	−107,747.90000	−107,728.30000
UBRE	0.02178	0.02184	0.02174

Notes: 0 '***' 0.001 '**' 0.01 '*' 0.05.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.regsciurbeco.2018.09.001.

References

Abbott, J., Klaiber, H.A., 2010. An Embarrassment of Riches: confronting omitted variable bias and multi-scale capitalization in hedonic price models. Rev. Econ. Stat. 93 (4), 1331–1342.
Ahlfeldt, G., 2011. If Alonso was right: modeling accessibility and explaining the residential land gradient. J. Reg. Sci. 51 (2), 318–338.
Anthon, S., Thorsen, B.J., Helles, F., 2005. Urban-fringe afforestation projects and taxable hedonic values. Urban For. Urban Green. 3, 79–91.
Bajari, P., Benkard, C.L., 2005. Demand estimation with heterogeneous consumers and unobserved product characteristics: a hedonic approach. J. Polit. Econ. 113 (6), 1239–1276.
Bajari, P., Kahn, M.E., 2005. Estimating housing demand with an application to explaining racial segregation in cities. J. Bus. Econ. Stat. 23 (1), 20–33.
Bartik, T.J., 1988. Measuring the benefits of amenity improvements in hedonic price models. Land Econ. 64 (2), 172–183.
Bartik, T.J., 1987. The estimation of demand parameters in hedonic price models. J. Polit. Econ. 95 (1), 81–88.
Bishop, K.C., Timmins, C., 2017. Estimating the Marginal Willingness to Pay Function without Instrumental Variables. Available at SSRN: https://ssrn.com/abstract=2748657 https://doi.org/10.2139/ssrn.2748657.
Brasington, D.M., Hite, D., 2005. Demand for environmental quality: a spatial hedonic analysis. Reg. Sci. Urban Econ. 35 (1), 57–82.
Chattophadyay, S., 1999. Estimating the demand for air quality: new evidence based on the Chicago housing market. Land Econ. 75 (1), 22–38.
Cho, S.-H., Jung, S., Kim, S.G., 2009. Valuation of spatial configurations and forest types in the Southern Appalachian Highlands. Environ. Manag. 43 (4), 628–644.
Danish Business Authority, 2011. The Central Company Register Danish Business Authority see. https://datacvr.virk.dk/data/.

Day, B., Bateman, I.J., Lake, I., 2007. Beyond implicit prices: recovering theoretically consistent and transferable values for noise avoidance from a hedonic property price model. Environ. Resour. Econ. 37 (1), 211–232.

Ekeland, I., Heckman, J.J., Nesheim, L., 2004. Identification and estimation of hedonic models. J. Polit. Econ. 112 (S1), S60–S109.

Epple, D., 1987. Hedonic prices and implicit markets: estimating demand and supply functions for differentiated products. J. Polit. Econ. 95 (1), 59–80.

ESRI 2011, 2015. ArcGIS Desktop, 10.2.1. Environmental Systems Research Institute, Redlands, CA.

Fleming, D., Grimes, A., Lebreton, L., Maré, D., Nunns, P., 2018. Valuing sunshine. Reg. Sci. Urban Econ. 68, 268–276.

Franco, S.F., Macdonald, J.L., 2018. Measurement and valuation of urban greenness: remote sensing and hedonic applications to Lisbon, Portugal. Reg. Sci. Urban Econ. online article (in press) at https://doi.org/10.1016/j.regsciurbeco.2017.03.002.

Heckman, J.J., Matzkin, R.L., Nesheim, L., 2010. Nonparametric identification and estimation of nonadditive hedonic models. Econometrica 78 (5), 1569–1591.

Jiao, L., Liu, Y., 2010. Geographic field model based hedonic valuation of urban open spaces in Wuhan, China. Landsc. Urban Plann. 98 (1), 47–55.

Jensen, C.U., Panduro, T.E., 2018. PanJen: an R package for ranking transformations in a linear regression. R J. 10, 13 (forthcoming).

Jensen, C.U., Panduro, T.E., Lundhede, T.H., von Graevenitz, K., Thorsen, B.J., 2016a. Robin Hood in Reverse? Assessing Distributional Effects of Green Space Policy Using a Second-stage Hedonic House Price Model. Working paper No. 2016/07. University of Copenhagen, Department of Food and Resource Economics.

Jensen, C.U., Panduro, T.E., J Thorsen, B., 2016b. The demand for urban diversity - a multiple markets approach. In: Presented at the ERSA Conference 2017.

Jensen, F.S., Koch, N.E., 2004. Twenty-five years of forest recreation research in Denmark and its influence on forest policy. Scand. J. For. Res. 19 (S4), 93–102.

Kong, F., Yin, H., Nakagoshi, N., 2007. Using GIS and landscape metrics in the hedonic price modeling of the amenity value of urban green space: a case study in Jinan city, China. Landsc. Urban Plann. 79 (3), 240–252.

Kuminoff, N.V., Parmeter, C., Pope, J., 2010. Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities? J. Environ. Econ. Manag. 60 (3), 145–160.

Lake, I.R., Lovett, A.A., Bateman, I.J., Day, B., 2000. Using GIS and large-scale digital data to implement hedonic pricing studies. Int. J. Geogr. Inf. Sci. 14 (6), 521–541.

Lundhede, T.H., Panduro, T.E., Kummel, L., Ståhle, A., Heyman, A., Thorsen, B.J., 2013. Værdisætning af bykvaliteter – fra hovedstad til provins (Valuation of urban qualities – from capital to province). IFRO Report 216 (a, b and c). Department of Food and Resource Economics, University of Copenhagen, p. 68.

Mansfield, C., Pattanayak, S.K., McDow, McDonald, R., Halpin, P., 2005. Shades of green: measuring the value of urban forests in the housing market. J. For. Econ. 11 (3), 177–199.

McFadden, D., 1973. Econometric models for probabilistic choice among products. J. Bus. 53 (3), S13–S29.

Netusil, N.R., Chattopadhyay, S., Kovacs, K.F., 2010. Estimating the demand for tree canopy: a second-stage hedonic price analysis in Portland, Oregon. Land Econ. 86 (2), 281–293.

Panduro, T.E., Thorsen, B.J., 2014. Evaluating two model reduction approaches for large scale hedonic models sensitive to omitted variables and multicollinearity. Lett. Spat. Resour. Sci. 7, 85–102.

Panduro, T.E., Veie, K.L., 2013. Classification and valuation of urban green spaces—a hedonic house price valuation. Landsc. Urban Plann. 120, 119–128.

Poudyal, N.C., Hodges, D.G., Merrett, C.D., 2009. A hedonic analysis of the demand for and benefits of urban recreation parks. Land Use Pol. 26 (4), 975–983.

R Core Team, 2015. R: a Language and Environment for Statistical Computing, 3.2.0. R Foundation for Statistical Computing, Vienna, Austria.

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

Sadayuki, T., 2018. Measuring the spatial effect of multiple sites: an application to housing rent and public transportation in Tokyo, Japan. Reg. Sci. Urban Econ. 70, 155–173.

Sander, H., Polasky, S., Haight, R.G., 2010. The value of urban tree cover: a hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA. Ecol. Econ. 69 (8), 1646–1656.

Schipperijn, J., Ekholm, O., Stigsdotter, U.K., Toftager, M., Bentsen, P., Kamper-Jørgensen, F., Randrup, T.B., 2010. Factors influencing the use of green space: results from a Danish national representative survey. Landsc. Urban Plann. 95 (3), 130–137.

The Danish Geodata Agency, 2011. Kort10, vol. 2011.

Toftager, M., Ekholm, O., Schipperijn, J., Stigsdotter, U.K., Bentsen, P., Grønbæk, M., Randrup, T.B., Kamper-Jørgensen, F., 2011. Distance to green space and physical activity: a Danish national representative survey. J. Phys. Activ. Health 8 (6), 741–749.

Tyrväinen, L., Miettinen, A., 2000. Property prices and urban forest amenities. J. Environ. Econ. Manag. 39 (2), 205–223.

von Graevenitz, K., Panduro, T.E., 2015. An alternative to the standard spatial econometric approaches in hedonic house price models. Land Econ. 91 (2), 386–409.

von Graevenitz, K., 2018. The amenity cost of road noise. J. Environ. Econ. Manag. 90, 1–22.

Wood, S.N., 2006. Generalized Additive Models: an Introduction with R, second ed. Chapman and Hall/CRC, p. 476.

Zhang, C., Boyle, K.J., Kuminoff, N.V., 2015. Partial identification of amenity demand functions. J. Environ. Econ. Manag. 71, 180–197.

Zhou, Q., Panduro, T.E., Thorsen, B.J., Arnbjerg-Nielsen, K., 2013. Adaption to extreme rainfall with open urban drainage system: an integrated hydrological cost-benefit analysis. Environ. Manag. 51 (3), 586–601.