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Analysis

Mixed monetary and non-monetary valuation of attractive urban green space: A case study using Amsterdam house prices

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ABSTRACT

This paper offers new insight into the monetary value of green space at the intra-urban level. To this end, an established monetary valuation method, hedonic price analysis, is integrated with a relatively novel non-monetary valuation method. In specific, online value mapping-based survey data ($N = 723$) are used to inform hedonic models of the preferences that potential home buyers may have for nearby attractive green spaces. The estimation uses data on 35,298 home transactions in the Amsterdam agglomeration's urban core. Homes nearby attractive green space are found to sell at a price premium, which decays with distance and becomes negligible after one kilometer. The estimated price-effect varies from 7.1%–9.3% for houses within 0.25 km from the nearest attractive green space to 1.7%–2.3% for houses located at 0.75–1.0 km away, depending on the scale at which omitted spatial variables are controlled for. Adding to the discussion of spatial controls in this type of analysis, the controls are evaluated at multiple scales and a metric that simplifies the interpretation of the scale of spatial controls – the mean equalized diameter – is introduced. This study's findings may inform policymakers who seek to maximize the well-being of urban citizens through public investments in attractive amenities.

1. Introduction

While processes of urbanization persist across the world, the valuation of urban green spaces remains ‘an open frontier’, one which attracts intensive academic interest (Gómez-Baggethun and Barton, 2013). An important rationale for this interest in valuation is rooted in the absence of a market for the Ecosystem Services (ESS) that urban green spaces provide. Green spaces may provide various ‘services’, see TEEB (2010), including Provisioning ESS, such as food production or sewage treatment (e.g., Bolund and Hunhammar, 1999); Regulating ESS, like air filtering or storm water attenuation (e.g., Jim and Chen, 2008); Supporting ESS, such as nutrient cycling or photosynthesis (e.g., Jim and Chen, 2008); or Cultural ESS, by offering space for recreation or enjoyment of aesthetic landscapes (Daniel et al., 2012; Kulczyk et al., 2018; Scholte et al., 2015). However, apart from the provisioning services, the value of ESS is not clearly observable in markets and both monetary and non-monetary valuation methods can be used to make value estimates (De Groot et al., 2002; Fisher and Turner, 2008; Sijtsma et al., 2013). Even so, full quantification of ESS value is a huge and complex challenge, both ecologically and socio-culturally (Admiraal et al., 2013; Mace et al., 2012; Scholte et al., 2015). In this paper, we will limit ourselves to one of the fairly straightforward valuation

options, which infers the value of ESS from a market in which these ESS are implicitly traded.

Our analysis considers the housing market, which has over recent decades, and up to the present, been considered by many studies that sought to infer how green space is implicitly valued by those who live in cities (Czembrowski et al., 2016, 2019; Daams et al., 2016; Liebelt et al., 2018; Panduro and Veie, 2013; Roebeling et al. 2016; Schläpfer et al., 2015; Xiao et al., 2016). Relevantly, housing market-based valuation, other than many ESS valuation studies, remains quite close to the economic domain in the sense that the population enjoying the benefits is limited, identifiable, and the services are mostly of a use or potential-use character (De Groot et al., 2002). However, besides the appeal of housing market analysis from a theoretical point of view, this market has a distinct characteristic that is important from a perspective of valuation: the housing market is one of the largest markets, in terms of capital value. Empirical estimates ascribe 86% of the total capital stock, or USD 249 trillion, in OECD countries to real estate—a major share of this capital value coming from housing (OECD, 2017).

Now, the way in which housing value may reflect green space crucially depends on how potential home buyers value green space's ESS. The relationship as such is widely established in the housing literature (McConnell and Walls, 2005; Waltert and Schläpfer, 2010;

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Brander and Koetse, 2011). Following most of the aforementioned literature, we focus on amenity value and not so much on regulating, supporting, or provisioning services. In particular, we focus on Cultural ESS that are defined as “nonmaterial benefits people obtain from ecosystems” and may be particularly related to recreation and aesthetic enjoyment (MEA, 2005, 40; Kulczyk et al., 2018). Hence, green spaces that are associated with recreational and aesthetic features of a high quality may attract additional bidders for nearby homes that are listed for sale—which may as a result sell at higher prices.

Outcomes of the abovementioned process may be revealed using the so-called hedonic model. The hedonic model decomposes the sales prices of homes into implicit prices for an observed set of house characteristics, including location relative to green space. Such estimation, however, requires a priori information about the determinants of house prices in order to specify the relevant variables as well as to operationalize them appropriately. This implies that, in the case of green space valuation, the hedonic model needs to be pointed towards those green spaces that have a certain quality that leads potential home buyers to consider them in their purchase decisions. Indeed, the hedonic price model does not differentiate between Provision, Regulating, Supporting, or Cultural ESS as a single green space may provide a multi-dimensional bundle of services. Moreover, Cultural ESS are not straightforward to associate with the (physical) characteristics of green spaces. As green spaces can be highly heterogeneous, even expert assessments of the perceived quality of green spaces tend to show considerable levels of disagreement (Daniel, 2001). Despite this situation, hedonic valuation studies continue to consider only physical land use types in their classification of observed green spaces; see, for example, the literature review in Waltert and Schläpfer (2010). Instead, borrowing words from Lancaster (1966, 134), whose consumer theory underpins modern hedonic analysis of house prices, in this paper we “proceed to look at the situation in much the same way as the consumer—or even the economist, in private life—would look at it.”

The objective of this study is to estimate more accurately the value of the cultural ecosystem services of green space from urban residential property prices, by combining an established monetary valuation method, hedonic pricing, with a relatively novel non-monetary valuation method, online value mapping—Participatory GIS (PGIS) surveying (Brown and Fagerholm, 2015; Brown and Kytä, 2014). The role of hedonic pricing is to disentangle urban house prices into implicit prices for house characteristics that are *objectively* discernable, including proximity to green space. But, before doing so, PGIS survey data are used to ‘inform’ the hedonic model of the *subjective* preferences that residents have for individual green spaces. This then targets the hedonic model towards those green spaces that potential home buyers, whose interactions determine house prices, are likely to consider in their purchase decisions. Doing so may sharpen the house price-based valuation of environmental amenities, as proposed in the technical review of the hedonic literature in Palmquist (2005).

The integrated monetary and non-monetary valuation of green spaces in residential areas, such as in our study, can be traced back as far as to Earnhart (2001). However, the empirical integration of this kind has since 2001 been applied only in recent house price studies. The recent studies that have done so, the studies by Czembrowski et al. (2016) and Daams et al. (2016), serve as a starting point for this paper's empirical design and its specific intra-urban focus.

Daams et al.'s (2016) study of houses across the Netherlands indicates price effects ranging from 16%, for houses < 0.5 km from attractive green space, to 1.6%, for houses 7 km away. Their findings demonstrate that land use data are insufficient to categorizing green spaces by their level of amenity as perceived by home buyers: (PGIS) data on how distinct green spaces are perceived by residents are needed to enrich land use data as their results become spurious when using measures based only on land use data. However, their main analysis considers a national selection of most attractive green spaces, which are mostly outside of cities.

An urban study area, however, is investigated in Czembrowski et al. (2016). Their study combines land use data and PGIS data, in a way similar to Daams et al. (2016), focusing on the city of Łódź in Poland. The sign and magnitude of their estimates for a range of more and less attractive green space types' impact on house prices are mixed. While estimates of impacts on house prices, in terms of sign and direction, are found to be consistent with the PGIS survey outcomes, they also find notable exceptions. For instance, attractive forests are documented to have no impact on house prices, in contrast to a positive estimated price effect for forests that receive neutral appreciation in the survey. The authors point to “a typical trade-off between different value perspectives” as the underlying cause and note these results were “rather unexpected” (Czembrowski et al., 2016, 172–173)—which warrants further intra-urban study.

This study, at the intra-urban level, extends the Czembrowski et al. (2016) and Daams et al. (2016), as well as the Earnhart (2001) and Palmquist (2005) studies, by focusing on hedonic house price valuation of green space using an integrated monetary and non-monetary valuation. Indeed, integrated valuation studies, however promising (c.f. Palmquist, 2005), are sparse at the intra-city level (c.f. Czembrowski et al., 2016 and Daams et al., 2016), which calls for further evidence on how perceived green space amenities are valued within urban areas. This urban focus is particularly relevant for urban planning and conservation policy, given ongoing urbanization processes in the long term, alongside green space's relative scarcity in cities.

Importantly, besides that we crucially identify the locations of those urban green spaces that are likely particularly valuable to home buyers, our hedonic approach is spatially explicit in three additional ways. First, as green space valuation practices and policy analysis require a precise estimate of the distance across which green space has an effect on house prices, as such estimate is central to the determination of aggregate value impacts, we allow effects to vary with distance – and also estimate the distance after which the effect, if any, becomes negligible. This, moreover, allows us to investigate what distance-specific effects are obtained when varying a part of our econometric model's specification that is of key importance, the spatial controls.

Second, spatial controls are evaluated at varying scales (e.g., at different zip code levels), as recommended in earlier hedonic studies of green space (Abbott and Klaiber, 2011; Daams et al., 2016; Von Graevenitz and Panduro, 2015). Indeed, a hedonic study needs to control for many characteristics of houses and their locations that are correlated with the variable of interest. As not all of such variables can be observed, this may give rise to omitted variable bias, a common problem with hedonic models (Kuminoff et al., 2010). Hence, spatial controls have become an important way to account for confounding omitted spatial variables (e.g., neighborhood characteristics such as similar-style architecture of homes or shared cultural values amongst inhabitants). However, if the spatial controls are too broadly defined, they may not mitigate omitted variable bias effectively. On the other hand, when spatial controls are defined using a too-fine scale, spatial controls may over-reduce the variance of the data so that the actual impact of green space on house prices is underestimated (Abbott and Klaiber, 2011). Such spatial control scale-issues confound interpretation of the above-mentioned ‘mixed results’ in Czembrowski et al. (2016), as sensitivity to changes in the scale of controls for omitted spatial variables is not explicitly evaluated. As a correct spatial scale of the controls is not known a priori, the hedonic pricing literature advises to inspect model results for distinct scales of the spatial controls and then select the scale that is empirically most accurate and convincing. This is the approach we take in our analysis to evaluate the scale at which spatial controls become too tight and absorb the attractive green space's price-effect, as well as to pinpoint which model(s) potentially provide(s) the most accurate results. As part of this, we introduce a simple new metric, the mean equalized diameter (MED) of spatial control areas, to improve the interpretation of the scale of spatial controls.

Fig. 1. Schematic visualization of the study's methodological design.

Third, our valuation study of green space considers the case of the high-density urban core of the Amsterdam agglomeration (the Netherlands), as defined by the OECD (2012). This OECD-definition allows for the international comparison of our study area's characteristics, such as its density.¹ Indeed, this way of defining the study area prevents the artificial definition of the spatial extent of the housing market under study, for example when based on administrative borders, by considering agglomeration—which is also the scale at which market forces shape house prices. Hence, the agglomeration-based delineation of our study area, lays a basis for future cross-city comparison of hedonic green space valuations in an internationally consistent way. With specific regard to Amsterdam, it is noteworthy that this city's development policy, in line with Dutch policy more generally, is characterized by the strict use of land use controls to contain urban expansion or densification (De Roo, 2000). By implication, the supply of urban green space is relatively stable and green spaces are predominantly public amenities and thus suitable for our hedonic analysis.

The remainder of this paper is organized as follows: in the next section we operationalize attractive green spaces and describe the housing transaction data. Section 3 specifies the hedonic models. The results are discussed in Section 4, followed by concluding remarks in Section 5.

2. Materials and methods

2.1. Study design

Our study considers non-monetary information of people's spatially explicit preferences for regionally attractive green space, as captured in PGIS data. PGIS data are spatially clustered, using established DBSCAN (see Section 2.2) clustering techniques from outside the field of green space assessment, to obtain hotspots of green space appreciation. By doing so, we

construct a measure of 'attractive regional amenities' amongst our study area's green spaces. This measure serves as a proxy for the aggregated perception of such amenities by potential home buyers and is included in hedonic models. This effectuates our study's integration of non-monetary and monetary methods for green space valuation (see Fig. 1).

Hedonic models are used to investigate the magnitude of house price impacts as well as any distance decay of the implied Cultural Ecosystem Services, by establishing the distance after which the effect of attractive green space on house prices becomes negligible. How the results may be influenced by the scale of controls for omitted spatial processes is evaluated. As part of this evaluation, the spatial controls are interpreted using the mean equalized diameter (MED) metric which this study introduces. The MED metric quantifies the size of the observed spatial control areas, thereby allowing comparison across models or studies. The analysis aims to reveal the monetary value of the stock² of attractive green spaces that are perceived as quality amenities at the regional scale.

2.2. Measurement of attractive green spaces

Attractive green spaces are defined spatially by combining land use data with spatial clusters of PGIS survey data. This is done in two steps. The first step is the clustering of the PGIS point-coordinate data, which reflect the locations of attractive green space designations by survey respondents, following Daams et al. (2016). To perform the clustering, we apply an R implementation of the so-called Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm that was introduced in Ester et al. (1996). DBSCAN is a density-based unsupervised clustering algorithm which, based on a given set of point-coordinates, groups points that have

¹ For comparison, consider that in 2015 the Amsterdam agglomeration had a population density of 812 inhabitants per km² (at the FUA-level; as captured in the OECD Metropolitan eXplorer; accessed on 28 February 2019). This density is in relatively close range of the density of Paris (994 inhabitants per km²), far lower than Tokyo's density (3123 inhabitants per km²), and considerably higher than the density of Los Angeles (212 inhabitants per km²).

² Some studies have instead focused on the valuation of changes in parts of the supply of green space. Doing so may call for quasi-experimental study designs. For example, Heckert and Mennis (2012) study the economic benefits of vacant lots that have been 'greened' using a difference-in-differences specification. Similarly, Livy and Klaiber (2016) study whether house prices reflect the new creation of parks or playgrounds using augmented repeat sales specifications. Whereas such studies aim to exploit variation in house prices nearby a subset of green spaces that have undergone change, our study values the existing stock of attractive green space in a cross-sectional setting.

many nearby neighbors and sets aside points that lie alone in low-density regions; i.e. whose nearest neighbors are relative far away. The main advantages of DBSCAN over other clustering techniques, notably the often-used K-means and kernel density techniques (e.g., Anderson, 2009), are that the number of clusters in the point-data do not need to be defined a priori and that clusters can assume any spatial shape. Moreover, DBSCAN is discriminative: unlike clustering methods that partition entire samples into clusters, including K-means, DBSCAN categorizes points isolated in space as ‘noise’. Accordingly, DBSCAN is preferred on a theoretical basis. Indeed, the situation in which isolated PGIS data-points are forced into the nearest -but possibly far away- cluster, distorting its shape and distance to houses, is prevented by allowing for noise in the data. Hence, the algorithm may obtain those areas where PGIS designations of attractive green space are actually spatially concentrated. The DBSCAN algorithm, which involves basic machine learning, is well established in the fields of data mining³ and biomedicine, see Spahn et al. (2016) and Taskesen et al. (2016), but to our knowledge has not seen earlier application in hedonic studies or green space valuation studies.

DBSCAN builds on two parameters: the distance radius ‘*epsilon*’ and the minimum number of points required to form a dense region ‘*minPts*’. Clustered points are those that are in locations where the number of points, including the observed point itself, within *epsilon* distance is equal to, or larger than, *minPts*. Also included in clusters are points in locations within *epsilon* distance from a readily clustered point but where the *minPts* condition is not met. Only clustered points are kept to mitigate spurious patterns in the value mapping data, if any.

As we apply DBSCAN to our value mapping data, we specify its two parameters in the following way. *MinPts* is set to 4 following the Ester et al. (1996) rule of thumb that clustering is at minimum present when the number of points within *epsilon* distance from an observed data-point exceeds the number of dimensions of the data (latitude and longitude). An advantage of this parameter setting is that it ensures that green spaces are perceived as attractive by multiple PGIS respondents, while mitigating the influence of erroneous single designations, if any. *Epsilon* (in meters) is chosen from a range of distance values (250, 300, ..., 750 m) by maximizing average silhouette coefficient (SC; introduced in Rousseeuw, 1987). The average SC evaluates the tightness and separation of clusters and is a common metric of clustering quality (e.g. Taskesen et al., 2016). For the *i*th observed transaction, SC is given by

$$SC(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \quad (i)$$

where *a(i)* denotes the average distance of PGIS point *i* to all other PGIS points in its own cluster; *b(i)* gives the average distance of point *i* to all points in the cluster that is nearest to point *i*'s cluster. A high SC suggests that observed point *i* is assigned to the correct cluster, whereas a low SC suggests that point *i* may cohere with the nearest cluster more than with its own cluster. SCs can range from -1 to +1, where a higher value indicates a better fit of clusters on the data.

In the second step of our procedure we combine the clusters that are based on PGIS data with Statistics Netherlands 2010 land use data. Land use categories include parks, recreation areas, forests, water bodies, open wet nature, and open dry nature. Thus, we assume a broad definition of green space, as it may include any features that could be perceived as ‘natural’. Which (mixes) of these natural features give shape to coherent attractive green spaces is allowed to depend on the perception of PGIS survey respondents: similar to Daams et al. (2016), all of the observed land use features that contain at least one clustered value mapping marker are kept.

³ The contemporary relevance of the 1996 algorithm is further illustrated by the 2014 ‘Test of Time’ Award that DBSCAN received from the academic community behind the KDD, a leading conference on data mining.

2.3. Attractive green space data

We draw from the database of the Greenmapper (earlier called Hotspotmonitor) PGIS-based survey (www.greenmapper.org). The Greenmapper survey asks respondents to designate, on an online scrollable map, green spaces that they perceive as ‘attractive, valuable, or important’ (De Vries et al., 2013; Bijker and Sijsma, 2017). The map uses the Google Maps satellite view for maximum orientation. An attractive green space is allowed to be on land or water, should include features that can be broadly considered to be ‘natural’, and may be inside either rural or urban areas. In urban areas, where green spaces may be relatively small, a high accuracy of designations is allowed as the Greenmapper interface based on Google Maps enables smooth panning and adjustment of zoom levels. Designated locations are saved in the form of X,Y point-coordinates. In distinct steps, respondents are asked to ‘mark’ attractive green spaces at different spatial scales (local; regional; national; and global). National Greenmapper markers have been applied in a variety of studies, including a hedonic study of house prices (Daams et al., 2016). Markers on other spatial scales have been used in non-hedonic valuations of green space (Bijker and Sijsma, 2017; Daams and Sijsma, 2017; Daams and Veneri, 2017; Scholte et al., 2018; Sijsma et al., 2019).

This study uses a sample of Greenmapper markers that have been placed on green spaces at the ‘regional scale’ (*N* = 723).⁴ Regional scale is defined as the area that is within a 20 km radius from a Greenmapper respondent's home. As respondents are sampled from across the study area (see Fig. 2), this radius may in most cases cover most of the study area. The consequences of having some variation in coverage are limited as the definition of clusters of Greenmapper point-data is based on a minimum threshold of only four points that are nearby to each other. Furthermore, 86% of the observed markers is placed by respondents to stratified surveys (Daams et al., 2016). These stratified surveys were mainly conducted amongst members of the Growth for Knowledge (GfK) Internet panel, the spatially most comprehensive internet panel in the Netherlands.

The sample of observed markers consists only of markers that have been placed by residents of the urban core of the agglomeration of Amsterdam—as we also observe only the prices of houses within the same urban core. Amsterdam's urban core is delineated using the OECD-EU definition of functional urban areas (FUAs). FUAs define boundaries of urban areas in a way that ensures a high level of comparability across countries. The ‘functional’ aspect of FUAs is that urban areas are defined as economically integrated areas, as they comprise at least one urban core (based on population density) as well as a surrounding commuting zone (based on commuter flows). Therefore, a FUA can be considered as a spatial unit of a ‘daily urban system’.⁵ This agglomeration-based definition of the study area helps to prevent

⁴ The 723 markers in the study area are derived from all Greenmapper datasets available as of March 2017. The earliest amongst these datasets originates from 2010. Most data, 623 respondents (86%), come from datasets generated through the GfK services, which aim to be representative selections of GfK members across the targeted study area. Of the GfK survey-based data records, 328 (45%) are analyzed in De Vries et al. (2013); 78 records (11%) in Bijker et al. (2017); and 217 records (30%) in Daams et al. (2016). The remaining 14% of records, which come from non-GfK surveys, comprise of 92 records (13%) from a dataset that resulted from a survey amongst members of Natuurmonumenten (the largest private Dutch nature conservation organization), and is analyzed in Davis et al. (2016), whereas the remaining 1% of the non-GfK records come from open crowdsourcing. All datasets except the crowdsourced dataset are analyzed in Daams et al. (2016), who consider only national level markers.

⁵ The FUA definition is also used in Daams et al. (2016). Their study finds that FUAs are useful subnational market definitions when assessing the amenity value of green space. Their analysis assesses how the value of (national very attractive) green space varies between different-sized urban areas and less densely populated areas.

Fig. 2. Spatial visualization of the study area and data.

underestimation of green space's amenity value, which might arise from small sample size, see Kuminoff et al. (2010), or too narrow definition of the housing market's extent as then effects may remain unobserved if they are shared amongst all houses (Graves, 1983). Moreover, the FUA scope mitigates influence from artificial definition of the housing market under study, as this internationally recognized definition of where the city ends is little sensitive to administrative boundaries. Noteworthy is that while only transacted houses in Amsterdam's urban core are observed, the buyers of these homes may enjoy the benefits of attractive green spaces that are outside of this urban core. Hence, Greenmapper markers are observed across Amsterdam's entire FUA (see Fig. 2).

The observed sample of Greenmapper markers is processed using

the procedure described in Section 2.1. In the DBSCAN-based clustering, an epsilon distance of 650 m is selected from the observed range of possible epsilon values based on silhouette score maximization ($SC = 0.72$). Of the 723 observed Greenmapper markers, 63.1% is assigned to a cluster—and thus subsequently combined with land use data. The land use areas of the final attractive green spaces ($N = 29$), amounting to an area of 12,245 ha, are shown in Fig. 2.

2.4. Transaction data

House price data were obtained from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM). The NVMs database has recorded approximately 80% of all sales on the Dutch housing market in recent years. After cleaning the data,⁶ the observations in our sample cover 35,298 transactions of single-family houses inside the Amsterdam functional urban area's core (see Fig. 2), over January 2009 to December 2015.

Property characteristics measured in the data include transaction price and date as well as several structural characteristics: living area, parcel size, number of rooms, period of construction, type of heating, type of structure (detached, terraced etc.), and the presence of insulation materials. The data also have measured whether the land on which the house is located is leasehold property as well as address information including zip code and house number. This address information is used to geocode each observation at building-level using data from the Registers for Addresses and Buildings (BAG), which is obtained from the Netherlands Cadastre, Land Registry and Mapping Agency. We understand that people may value a portfolio of natural places, from local to global levels, but we also see empirically that regional places are visited frequently (Bijker and Sijtsma, 2017). Given the scarcity of attractive green spaces in the urban context this study considers, home buyers are likely to give high importance to the proximity to the nearest attractive green space. Our use of clusters of attractive green space markers leads to identification of areas that are perceived attractive (or important, valuable). Using regional markers to do so allows for a clear identification of appreciated places at the regional scale; our main point of interest. This means that, compared to all land use which classifies as nature, we focus on nature of serious quality – given its attractiveness to people. Based on address locations we measure each house's Euclidean distance to the nearest attractive green space. This distance measure is then discretized at the six distance intervals reported in Table 1, which provides descriptive statistics for the estimation sample.

3. Empirical models

3.1. Baseline hedonic specification

The effect of perceived regional green space amenities on the prices of nearby homes is identified using a hedonic multivariable regression model. To allow assessment of model stability we first construct a baseline specification that excludes the variable of interest.

We work with the Pseudo-Repeat Sales (Ps-RS) model. The Ps-RS model is similar to the standard hedonic model that includes spatial fixed effects, but is slightly stricter, as it applies spatial first differencing to the observed data (Kuminoff et al., 2010). Spatial differencing is an established strategy to reduce bias from omitted variables—see, for

⁶ The data are cleaned as follows: sales prices in the lower and upper 0.5% tails of the price-distribution are removed, observations with incomplete information on the observed property characteristics are removed, observations for idiosyncratic property subtypes (mobile homes, house boats, recreational homes, estates, care homes) are culled. Furthermore, we keep only observations of permanently inhabited houses that have transacted in the secondary market.

Table 1
Descriptive statistics for the estimation sample ($N = 35,298$).

Variable	Mean	St. Dev.
Price (euros)	274,122.00	188,688.70
Floor space (m ²)	125.88	39.84
Number of rooms	4.86	1.21
Parcel size (m ²)	220.28	490.50
End-of-terrace house	0.21	0.41
Terraced house	0.58	0.49
Duplex house	0.03	0.16
Semidetached house	0.11	0.32
Detached house	0.07	0.26
Constructed < 1906	0.03	0.18
Constructed 1906–1930	0.08	0.27
Constructed 1931–1944	0.05	0.23
Constructed 1945–1959	0.06	0.24
Constructed 1960–1970	0.09	0.28
Constructed 1971–1980	0.11	0.31
Constructed 1981–1990	0.21	0.41
Constructed 1991–2000	0.21	0.41
Constructed > 2000	0.16	0.37
Leasehold property	0.15	0.36
Central heating	0.95	0.22
Insulation	0.86	0.34
Year of transaction 2009	0.13	0.34
Year of transaction 2010	0.12	0.33
Year of transaction 2011	0.11	0.32
Year of transaction 2012	0.12	0.33
Year of transaction 2013	0.12	0.32
Year of transaction 2014	0.17	0.38
Year of transaction 2015	0.22	0.41
Distance (km) to AGS < 0.25	0.06	0.23
Distance (km) to AGS 0.25–0.50	0.06	0.23
Distance (km) to AGS 0.50–0.75	0.07	0.26
Distance (km) to AGS 0.75–1.00	0.08	0.28
Distance (km) to AGS 1.00–1.25	0.08	0.27
Distance (km) to AGS > 1.25	0.66	0.47

Note: AGS is an abbreviation of ‘attractive green space’.

example, the technical review of (spatial) econometric approaches by Gibbons and Overman (2012).⁷ In our analysis, first-differencing is used as a spatial fixed effect design. In specific, first differencing is applied to houses that are paired for having location in the same ‘neighborhood unit’ (e.g., zip code areas) that the model observes. As a result of this, the Ps-RS model cancels out local similarity in the prices, similar to a standard spatial fixed effect model, but also cancels out local similarity, if any, in the unobserved characteristics of (paired) houses (Guo et al., 2014). Such unobserved characteristics may include any of the characteristics that are not amongst our model’s control variables (e.g., architectural style, school quality, or distance to the city center or public transport hubs). Possible effects from such site-specific characteristics are controlled for at, or above, the level of the spatial unit of first-differencing, similar to common spatial fixed effect models (Abbott and Klaiber, 2011; Gibbons and Overman, 2012). Such fixed effect-based design is a preferred approach to purge the influence of variables that are possibly locally correlated with an environmental variable of interest from hedonic estimation (Kuminoff et al., 2010).

Baseline model (1) can be specified as

$$\ln P_a - \ln P_b = \alpha + \sum_{k=1}^K \beta_k (X_{a,k} - X_{b,k}) + \varepsilon_{a,b} \quad (1)$$

where α is the constant; $\ln P_{a,l}$ and $\ln P_{b,l}$ are the natural logarithms of the transaction prices of house a and house b which are paired, while both have been sold within the functional urban area core of Amsterdam; $X_{a,k}$ and $X_{b,k}$ the k th house characteristic ($k = 1, \dots, K$), including the year of transaction; and $\varepsilon_{a,b}$ denotes spatially clustered

standard errors.

It may be noted that baseline model (1) accounts for possible spatial autocorrelation of house prices. Such spatial structure in house prices may be present in the data as sellers or real estate agents who set listing prices may consider the selling prices of nearby houses. In addition, prices may be similar locally when houses have similar structural characteristics, for example as they were developed in the same period, or when locational amenities are shared. It is well-documented that such spatial structure may be reflected in house prices in general, see Anselin and Le Gallo (2006) or Conway et al. (2010), as well as in house prices in the Amsterdam region (Lazrak et al., 2014). Hence, spatial autocorrelation is accounted for in our models as we further explain below. We may first note that, to some extent, the first-differencing accounts for some of the local correlations between house prices. In this context, model (1) serves as a baseline prior to the evaluation of spatial controls. Indeed, the main specifications control for fine spatial fixed effects, through spatial first-differencing at fine intra-urban scales. However, below the spatial scale of the first-differencing, spatial error dependence might remain. Similar to Heintzelman and Tuttle's (2012) spatial fixed effects design, this is accounted for through the clustering of standard errors at the level of 6-digit zip codes (i.e., approximately at or below street level). This complementary model feature is implemented consistently across all of this study's models.

3.2. Main hedonic specifications

We now turn to models (2) to (5), which include measures of proximity to the nearest attractive green space. These attractive green spaces are measured, as explained above, combining land use data with PGIS survey data. The observed (single) measure is holistic as explained in Section 2.2. It should be noted that, following Palmquist's (2005) suggestion, attractive green space is measured from the perception of the residents in the urban area under study and not specifically the perception of the actual buyers. In contrast to disaggregated measures, a single holistic measure offers the practical advantage that it mitigates possible issues of “multi-collinearity that often plague environmental valuation studies” (Pendleton and Shonkwiler, 2001, 128). The main hedonic specification's basic structure, which is allowed to vary across models (2) to (5) assume distinct scales of spatial controls, is expressed as

$$\ln P_{a,l} - \ln P_{b,l} = \alpha + \sum_{k=1}^K \beta_k (X_{a,k,l} - X_{b,k,l}) + \sum_{m=1}^M \beta_l (A_{a,m,l} - A_{b,m,l}) + \varepsilon_{a,b,l} \quad (2)$$

where $A_{a,m,l}$ and $A_{b,m,l}$ are vectors of dummy variables that capture the discrete distance to the nearest attractive green space in intervals of 0–0.25 km; 0.25–0.50 km; 0.50–0.75 km; 0.75–1.00 km; and 1.00–1.25 km⁸; and l indexes ‘neighborhood’ areas within which house a and house b are paired, being the entire core of the functional urban area of Amsterdam in the case of (1) and (2), 4-digit zip code areas in model (3), 5-digit zip codes in model (4), and 6-digit zip codes in model (5).

The above means we explicitly vary the size of the ‘neighborhood unit’ l in order to discover the appropriate level of ‘spatial controls’ for

⁷ An additional benefit of spatial first-differencing in a fixed effect design is that computational costs are minimal (Pace and Barry 1999).

⁸ We use discrete measures of distance, following Daams et al. (2016). Discrete distance is measured in 0.25 km intervals as these may include sufficient observations, while being of sufficient spatial precision for the analysis of distance decay and large enough to capture variation in distance to attractive green space that is economically meaningful. Initial regression models, which include discrete 0.25 km distance intervals up to 5 km, indicate that the effect of attractive green spaces on house prices becomes negligible after 1 km. Hence, the main specification includes only dummies up to 1.00 km as well as a dummy for 1.00 km to 1.25 km in order to reveal the distance after which the effect stops.

omitted spatial processes - which may otherwise confound the estimation. This is important because, as discussed above, the scale of the omitted spatial processes that need to be controlled for is not known a priori (Abbott and Klaiber, 2011; Von Graevenitz and Panduro, 2015).⁹ Dutch zip code areas are useful for this multi-scale procedure as smaller zip code areas have a perfect fit within the boundaries of larger zip code areas. It may be noted that, model (2), like model (1), merely gives a baseline prior to the introduction of intra-city spatial controls.

Geometric characteristics of the spatial controls, as well as variation in proximity to green space that remains in the estimation data after spatial first-differencing, will be reported to enhance interpretation of model results. We propose 'mean equalized diameter' (MED) as a unit for standardized reporting of the scale of spatial control areas. This measure is the hypothetical diameter (in kilometers) of a circle that reflects the mean size of observed spatial control areas.

We expect that attractive green spaces have a positive impact on urban house prices as residents of the study area have stated in the Greenmapper PGIS survey that they perceive these green spaces as regional amenities. In addition, in line with Daams et al. (2016), we expect that effects on house prices decrease with distance to the nearest attractive green space and becomes negligible beyond a certain distance. We expect that the narrowing down spatial controls across models (3), (4), and (5) will at first lead to more precise estimates due to the introduction of finer-scale spatial controls, but that at some point these controls will become over-precise and absorb actual price-effects of proximity to attractive green space.

4. Results

4.1. Results for baseline specification

Table 2 reports the results for our five model specifications. The models indicate joint significance for each of the specifications.¹⁰ Let us first consider the results for baseline model (1) without spatial controls or measures of proximity to attractive green space. Most of the estimates are as expected. Premiums on house prices are found for larger houses in terms of living area and number of rooms. The presence of central heating leads to a higher house price, and the type of structure matters as well in the marketplace, as detached houses are shown to sell at higher prices than other house types. Estimates for the observed periods of construction, parcel size, property leaseholds, and the presence of insulation appear to be misestimated in this first rough model. For example, better-insulated homes are estimated to not sell at a premium price and leasehold status is estimated, everything else held constant, to lead to a considerably higher sales price – both in contrast to basic economic theory. However, the estimates for these variables are as expected when spatial omitted variable processes are controlled for (models 3–5), which directly shows the need for spatial controls in this type of models.

⁹ It may be noted that statistical rules at the model level, for example rules based on information criteria, may not necessarily establish the 'best' amongst our models in an evident way, as these consider model performance at the global level, not at the level of the individual coefficients of interest. Indeed, the true capitalization of green spaces in home prices, as well its absorption by the spatial controls in the distinct models, is unknown. Hence, one model may 'outperform' another at the global level by better explaining house prices, but at the same time cancel out and underestimate the effect of green space more.

¹⁰ Noteworthy is that adjusted R^2 values are not directly comparable across the reported models due to the spatial first-differencing of variables at distinct spatial scales; this removes different amounts of variation from the data that could otherwise be (partially) explained by the models. It may also be noted that at finer scales fewer transactions are observed as for each zip code area the first included observation is eliminated.

4.2. Results for main specifications

Models (2) to (5) in Table 2 provide results for the main specifications which include measures of proximity to green spaces that residents of our study area perceive as attractive. This change in specification relative to the baseline model (1) has a minimal influence on the results for house characteristics other than the proximity measures. Let us turn to the effect of distance to the nearest attractive green space on house prices. This effect is estimated for discrete distance intervals that are captured in dummy variables. The estimated coefficients associated with these dummy variables are all statistically significant at the 1% level. As the specification of model (2) does not control for omitted spatial processes, the estimated effects of distance to attractive green space are expected to be biased and not relevant economically.

Let us now consider the results for model (3), which introduces spatial controls to our estimation, at the spatial scale of four-digit zip codes ($N = 200$). This model's estimation comes from within-zip code variation in capitalization of economic benefits of attractive green space into house prices. We can make three important observations. First, houses within 0.25 km from attractive green space are found to sell at 7.1% higher prices (relative to prices in the reference group of houses farther than 1.25 km away from attractive green space).¹¹

Second, in contrast to results for model (2) without spatial controls, in model (3) the price effect is found to decay smoothly with distance, from 7.1% to 1.7%, over a 0 to 1 km range. This change in effects – from unintuitive signs and effect sizes to economically intuitive ones – is essential and confirms the sensitivity of green space effect estimates to inclusion of spatial controls which we underlined so extensively.

Third, we find no significant price effect for houses 1 to 1.25 km away from attractive green space: this result indicates that regional level attractive green spaces do not capitalize in the prices of house farther than 1 km away. The finding of distance decay as such is consistent with results from an earlier study on (nationally) attractive green space and house prices, see Daams et al. (2016), as well as with studies the few other studies of urban green space that test for distance decay explicitly and find effects across several hundreds of meters (Conway et al., 2010; Panduro and Veie, 2013). The distance decay in the price effect is smooth and consistent and appears to depend on the green space's quality.¹²

We now turn to Fig. 3's report of $(e^{\beta} - 1)$ transformed coefficients in models (4) and (5), in which the spatial controls are tightened further to the spatial scales of 5-digit zip codes ($N = 1855$) and 6-digit zip codes ($N = 13,378$), respectively. Model (4)'s estimated price-effects for proximity to attractive green space are slightly higher, but broadly comparable, to those in model (3), as they show distance decay, from 9.3% to 2.3% across a 0 to 1-kilometer distance. In model (5), however, the estimated coefficients for the proximity variables are all insignificant, which suggests that in this model the effect of attractive green spaces has, effectively, been absorbed by its spatial controls.

¹¹ Note that the 7.1% price-effect is associated with the 0.068 coefficient in model (Anderson, 2009) in Table 2; across the reported models, coefficients for dummy variables can be interpreted as a percentage change in house price after a $(e^{\beta} - 1)$ transformation, given the model specifications' semilog functional form (Halvorsen and Palmquist, 1980).

¹² Indeed, Daams et al. (2016) document that in the case of nature that is (highly) attractive at the national level benefits of living close to nature are capitalized in the prices of houses at distance up to 7 km away from such nature. The distance decay found in the current study, for regionally attractive green space in an urban area, is more in line with the findings of the above-mentioned studies that also focus on urban green spaces. However, for example, Conway et al. (2010) note that their model's green space coefficients exhibit distance decay but not at a conventional level of significance, and may therefore not reflect a noticeable decay in price impacts, whereas the distance decay observed in the current study, although allowed to be non-linear, is smooth and consistent.

Table 2
Regression results of hedonic house price models.

	(1)	(2)	(3)	(4)	(5)
Dist. (km) to AGS < 0.25		0.019** (0.008)	0.068*** (0.010)	0.089*** (0.019)	0.022 (0.038)
Dist.(km) to AGS 0.25–0.50		0.020** (0.008)	0.027*** (0.008)	0.046*** (0.015)	0.004 (0.031)
Dist. (km) to AGS 0.50–0.75		0.019*** (0.007)	0.016** (0.007)	0.027** (0.013)	–0.006 (0.027)
Dist. (km) to AGS 0.75–1.00		0.067*** (0.007)	0.016*** (0.006)	0.023** (0.011)	0.001 (0.022)
Dist. (km) to AGS 1.00–1.25		0.053*** (0.007)	0.004 (0.005)	0.007 (0.009)	–0.002 (0.014)
Floor space (log)	1.129*** (0.010)	1.119*** (0.010)	0.714*** (0.007)	0.668*** (0.007)	0.590*** (0.012)
Number of rooms (log)	0.047*** (0.009)	0.045*** (0.009)	0.016*** (0.006)	0.023*** (0.006)	0.038*** (0.008)
Parcel size (log)	–0.003 (0.003)	–0.002 (0.003)	0.047*** (0.002)	0.041*** (0.002)	0.029*** (0.003)
Terraced house	–0.026*** (0.004)	–0.028*** (0.004)	–0.039*** (0.002)	–0.036*** (0.002)	–0.036*** (0.003)
Duplex house	0.087*** (0.010)	0.087*** (0.010)	0.098*** (0.006)	0.069*** (0.006)	0.019** (0.008)
Semidetached house	0.098*** (0.007)	0.101*** (0.006)	0.145*** (0.004)	0.133*** (0.004)	0.088*** (0.007)
Detached house	0.163*** (0.009)	0.168*** (0.009)	0.299*** (0.006)	0.276*** (0.007)	0.224*** (0.013)
Constructed < 1906	0.473*** (0.014)	0.465*** (0.014)	–0.201*** (0.013)	–0.219*** (0.015)	–0.166*** (0.028)
Constructed 1906–1930	0.184*** (0.009)	0.175*** (0.009)	–0.207*** (0.008)	–0.226*** (0.011)	–0.192*** (0.020)
Constructed 1931–1944	0.212*** (0.011)	0.201*** (0.010)	–0.146*** (0.008)	–0.182*** (0.011)	–0.140*** (0.021)
Constructed 1945–1959	0.223*** (0.009)	0.208*** (0.009)	–0.194*** (0.007)	–0.227*** (0.011)	–0.185*** (0.021)
Constructed 1960–1970	0.054*** (0.007)	0.051*** (0.007)	–0.216*** (0.006)	–0.225*** (0.010)	–0.163*** (0.020)
Constructed 1971–1980	–0.141*** (0.007)	–0.141*** (0.007)	–0.180*** (0.005)	–0.168*** (0.010)	–0.100*** (0.019)
Constructed 1981–1990	–0.121*** (0.006)	–0.123*** (0.006)	–0.140*** (0.004)	–0.127*** (0.008)	–0.053*** (0.014)
Constructed 1991–2000	–0.039*** (0.006)	–0.046*** (0.006)	–0.064*** (0.004)	–0.048*** (0.006)	–0.013 (0.010)
Leasehold property	0.202*** (0.005)	0.200*** (0.005)	–0.087*** (0.005)	–0.077*** (0.006)	–0.060*** (0.008)
Central heating	0.085*** (0.008)	0.084*** (0.008)	0.093*** (0.005)	0.096*** (0.005)	0.089*** (0.007)
Insulation	–0.000 (0.005)	0.003 (0.005)	0.034*** (0.003)	0.032*** (0.003)	0.031*** (0.004)
Constant	–0.000 (0.003)	–0.000 (0.003)	–0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Scale of spatial controls	City	City	4-digit zip code	5-digit zip code	6-digit zip code
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	35,297	35,297	35,098	33,443	21,920
Adjusted R ²	0.645	0.647	0.729	0.673	0.529
F Statistic	1578.2***	1324.2***	1842.6***	1156.2***	293.1***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of homes. The reference categories include distance to nearest attractive green space (AGS) > 1.25 km; end-of-terrace house; construction after 2000. Spatially clustered standard errors in parentheses.

*, **, *** Significance at 10%, 5%, and 1%, respectively.

Fig. 3. Percentage price effects and associated 95% confidence intervals.

The absorption of effects by spatial controls (in models 3 to 5) can be interpreted more clearly by considering Table 3. Table 3 shows that model (3)'s spatial controls, 200 zip code areas at the 4-digit level, when assumed to be of circular shape, have a mean equalized diameter (MED) of 1.31 km. This implies that at this scale of controls, sufficient variation in proximity to attractive green space may enter model (3)'s

estimation. Consider that, within an area that has a 1.31 km² diameter, one home can be 0.25–0.50 km away from the nearest attractive green space (which may be located outside of the scrutinized zip code area) while another home is 0.75–1.00 km away from the same attractive green space. Hence, a shift of one-unit in the distance interval-dummy variables is plausible at the scale of the spatial controls in model (3).

Table 3
Variation in spatial controls and estimation data.

Spatial scale	N areas	Mean equalized diameter (MED; km)	Share of homes paired within the same interval of distance to AGS	
4-digit zip codes	200	1.31	0.72	(Model 3)
5-digit zip codes	1855	0.43	0.86	(Model 4)
6-digit zip codes	13,378	0.16	0.96	(Model 5)

Notes: only zip code areas in the transaction data are considered. 'Mean equalized diameter' is the hypothetical diameter of a circle that reflects the mean size of the observed spatial control areas; the intervals of distance to attractive green space (AGS) are '0–0.25 km', '0.25–0.50 km', '0.50–0.75 km', '0.75–1.00 km', '1.00–1.25 km', and '> 1.25 km'.

This reduces concerns about absorption of effects by these spatial controls, even as we observe in the data for model (3) that a 0.72 share of home-pairs consists of homes that are in the same interval of distance to attractive green space.¹³ In model (3), more homes are paired within the same distance interval as the spatial control areas within which homes are paired are tightened (MED = 0.43 km) – but, the MED of the spatial control areas remains larger than the (0.25 km) segments of the distance intervals. This allows some variation in the estimation data to remain. In contrast, in model (Anselin and Le Gallo, 2006), much of the relevant variation in the estimation data is cancelled out due to the small size of its spatial control areas (MED of 0.16 km < 0.25 km segment).

Jointly interpreted, the results for all models, as reported in Tables 2 and 3, imply that models (3) and (4) most accurately estimate the ‘true coefficient’ of attractive green space on the prices of nearby homes.¹⁴ The percentage of the effect on house prices, for each of the observed distance intervals, is shown in Fig. 3 for both models (3) and (4), along with the associated 95% confidence intervals. It may be noted that the estimated effects obtained with model (3) are possibly noisier than those in model (4), which controls for omitted spatial processes more strictly. However, the relative narrower confidence intervals for model (3) suggest a higher accuracy than is obtained model (4). Model (4), however, offers a conservative bound as its spatial controls are at the finest scale before the scale at which attractive green space effects become fully absorbed by such controls (in model 5, as implied by the combined assessment of model results and MED values). Therefore, amongst models (3) and (4), there is strictly speaking no preferred model: the appropriate scale of spatial controls is unknown (c.f. Von Graevenitz and Panduro, 2015), which is precisely what warrants this study’s multi-scale approach.

5. Discussion

5.1. Economic valuation of ecosystem services

Economic valuation of ecosystem services has become a dynamic and productive field of science in the past decades, but in recent years several authors have stressed that we should be more aware of its limitations too. Norgaard (2010) in his seminal article argued that the humble economic metaphor of ecosystem services may be blinding “us to the ecological, economic, and political complexities of the challenges we actually face” (p. 1219), while Gómez-Baggethun and Ruiz-Pérez (2011) show that economic valuation may, due to its commodification of ecosystem services, be potentially counterproductive for biodiversity conservation and equity of access to ecosystem services benefits. We think our current analysis of economic valuation does not face these fundamental problems issues of valuation. Our study merely focuses on the cultural ecosystem service aspect of urban green space and, within that scope, mostly on the aesthetic and recreational value. Therefore, the valuation remains quite close to the economic domain in the sense that the population enjoying the benefits is limited and identifiable and the services are mostly of a use or potential-use character (De Groot et al., 2002). Furthermore, the market used for the hedonic valuation is in itself longer-term oriented, because when buying a house, people generally consider the benefits of (many) years to come, including the home’s rest-value after the potential sale. Within the complex spectrum

of ecosystem service valuation, see Pascual et al. (2017), this study is therefore on the simpler side; within the typology of 23 ecosystem services of De Groot et al. (2002, 397), we focus mainly on only one, (no. 19) ‘aesthetic information’, which has a clearly dominant way of valuation: hedonic pricing (see the scheme on the “relationship between ecosystem functions and monetary valuation techniques” in De Groot et al., 2002, 406). Still, this being said, one may be impressed by the many complexities that still had to be addressed (in this paper) before a solid valuation of only one ecosystem service, associated with a clear and comprehensively developed economic valuation method, could be achieved. This, in turn, may make one again ‘humble’ (c.f. Norgaard, 2010), when considering the potential for valuation of the other 22 ecosystem services – as those often come with less well-defined options for economic valuation.

5.2. Monetizing the ‘real estate value’ of green space

A growing literature on the hedonic valuation of real estate and land clearly shows the importance of green space as a driver of house prices. Indeed, houses that are nearer to green space than other houses have been widely documented to sell at relatively higher prices (e.g., Anderson and West, 2006; Brander and Koetse, 2011; Panduro and Veie, 2013). The price effect’s magnitude and distance decay have, in addition, been documented to vary with spatial context such as intra-urban, suburban or rural settings (e.g., Daams et al., 2016; Roebeling et al., 2016; Liebelt et al., 2018; Schläpfer et al., 2015; or Waltert and Schläpfer, 2010) and the quality of green space (Czembrowski et al., 2016; Daams et al., 2016; Earnhart, 2001). The current study further integrates these notions by using a refined empirical design which takes the spatially explicit and non-monetary valuation of green space as a basis, for a major metropolitan area in the Netherlands. In our report of results, we focused on the percentage of value that the observed green spaces add to the prices of nearby homes. The estimated economic benefits of living close to attractive green space are within the range of effects that McConnell and Walls (2005) tabulate in their review of findings in hedonic studies on green space. Based on the observed average home price of EUR 274,122, the estimates in models 3 and 4 imply an added value of proximity to attractive green space of about EUR 4493 (1.64%) to EUR 25,540 (9.32%), depending on how close the average priced home is to green space of such quality. In addition to this, one may note that, from the perspective of ecosystem valuation, the combination of the percentage of value-gain and the number of impacted homes is important: in our study 312,000 homes¹⁵ are impacted. In the high-density residential setting of a metropolitan area the monetary benefits across all properties nearby attractive green space may sum to a substantial value. The results imply that the per-hectare value of attractive green space may well exceed agricultural land values and that green space is less competitively positioned relative to urban land uses that have a more evident monetary value.¹⁶ Yet, in the literature, there is no absolute consensus on how to do the summation. Given the long-term impact of urban green space planning, for both current and future households, one can even argue that a correct summation would require insight not only into households’ current preferences for green space but also into their preferences in the long term—which are notoriously hard to predict and may extend beyond the expectations of the future that homebuyers may have at the time of sale (Daams and Sijtsma, 2017). However, keeping to current preferences, estimates of the aggregate housing value impacts of attractive green space relative to a situation where lesser or no green space is supplied should, according to Rosen’s (1974) seminal paper on hedonic pricing,

¹³ This share is 0.46 when no spatial controls are applied.

¹⁴ To provide some further assurance that our main models (Anderson, 2009) and (Anderson and West, 2006) appropriately control for omitted processes, we have re-estimated these models in an alternative type of specification which is close to quasi-experimental approaches. In these alternative specifications, the possible influence of time-varying spatial processes is controlled for at year-by-zip code level. The findings are similar to our main results and further confirm the ability of our main specifications to control for omitted processes (for additional information and model results, see Appendix).

¹⁵ As captured from the Netherlands Cadastre, Land Registry and Mapping Agency’s address-level register data.

¹⁶ In recent years, Dutch agricultural land values have been around EUR 60,000 per hectare (Kadaster, 2018).

be calculated from an area under a demand curve estimated in a second-stage hedonic model (for an example, see [Netusil et al., 2010](#)). Indeed, a non-marginal change in the supply of green space could, in turn, induce change in the sorting behavior of households and the equilibrium price schedule for nearby houses ([Palmquist, 2005](#)). While it appears relevant that the few studies that have considered such processes be extended, the current study leaves this for others.

5.3. Standardized interpretation of the scale of spatial controls

The methodological integration of the monetary hedonic valuation method and the non-monetary PGIS valuation method is powerful; however, this kind of hedonic model functions like a clockwork that requires a precise specification of its technical components. In that context, this study introduced a simple metric to enhance the interpretation of spatial controls (also commonly referred to as 'spatial fixed effects'), in terms of their scale, which is a relevant extra feature of the study but is also modest in its ambitions. Indeed, that the use of spatial controls, by itself, is a necessity has already been known since [Anderson and West \(2006\)](#). Their hedonic study showed that without spatial controls one might even estimate an incorrect sign for the effect of green space on house prices. This is echoed by our comparison of estimated price-effects of structural (non-green space) characteristics of homes across baseline models (1) and (2); only after inclusion of spatial controls estimates show the expected sign. This is also the point where the coefficients for attractive green space start to show the expected pattern of distance decay. As also shown in other studies, our findings underline that spatial controls should be applied at varying scales as the appropriate scale is unknown a priori ([Abbot and Klaiber 2011](#); [Von Graevenitz and Panduro, 2015](#)); results for models (3) to (5) indicate varying price-effect sizes, or even no effects at all when spatial controls become too-fine scale. However, unlike other hedonic studies of green space, ours has reported relatively detailed geometric information about the observed spatial controls to enhance the interpretation of their scale. The 'mean equalized diameter' of spatial controls was introduced to encourage other studies to report standardized information about their spatial controls. The importance of being specific about the characteristics of model controls has, in a similar vein, been raised in the field of political sciences ([Mummolo and Peterson, 2018](#)). Our study, however, makes an explicitly spatial case, that enables a simple understanding of the scale of spatial controls. Doing so may support a better founded interpretation of estimation outcomes in this type of studies.

6. Conclusions

This paper has combined an established monetary valuation

method, hedonic price analysis, and a relatively novel non-monetary valuation method, PGIS, in order to estimate more accurately the effect of green space on house prices within an urban environment. PGIS survey data were used to 'inform' hedonic models of the subjective preferences that potential home buyers may have for green spaces. More specifically, a proxy for attractive green spaces based on the aggregated perception of residents of the study area was related to the prices of nearby houses, using spatial first-differencing based Pseudo-Repeat Sales (hedonic) models. Our study connects the literature on the spatially explicit analysis of house prices with the growing literature on the integrated subjective and objective valuation of green spaces in an intra-urban setting.

Our findings show that attractive green spaces have significant impact on the prices of nearby houses within the urban core of the Amsterdam agglomeration. The estimated effect of attractive green spaces on house prices decays smoothly with distance and is explicitly estimated to become negligible for houses further than 1 km away. Depending on the spatial scale at which omitted spatial processes are controlled for, the estimated effect varies from 7.1%–9.3% for houses within 0.25 km from the nearest attractive green space to 1.7%–2.3% for houses located 0.75–1.0 km away. In addition, an incremental narrowing of spatial controls indicates the lower scale at which these controls are too tight for appropriate identification of amenity effects. Findings from this study may have implications for land use planning and public investment in green space in densely populated areas, where green space 'competes' with alternative land uses which have a more evident monetary productivity, such as infrastructure or real estate, for space and public investment. Hence, it is important to note that our findings may prevent the undervaluation of attractive green space's monetary value. Accurate information about green space's monetary value may help policy makers to maximize the well-being of urban citizens, as they decide on the amount of public investment that is directed towards the provision of attractive amenities.

Declaration of Competing Interest

None.

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Appendix A

In the hedonic literature on green space valuation, spatial fixed effect designs appear have, despite not always being evaluated appropriately, become common. In addition, quasi-experimental designs to identify effects of green space on house prices are becoming more popular as well ([Livy and Klaiber, 2016](#)). In this context, for extra evaluation of the main results, we present results for re-estimations of models (3) and (4) in alternative specifications (A) and (B), respectively ([Table A1](#)). The models address possible bias from omitted processes in a way that is both within this paper's methodological realm and close to quasi-experimental methods.

Table A1
Regression results, alternative model specifications.

	(A)	(B)
Dist. (km) to AGS < 0.25	0.077*** (0.010)	0.089*** (0.020)
Dist.(km) to AGS 0.25–0.50	0.039*** (0.007)	0.068*** (0.016)
Dist. (km) to AGS 0.50–0.75	0.026*** (0.007)	0.046*** (0.014)
Dist. (km) to AGS 0.75–1.00	0.025*** (0.006)	0.030** (0.012)
Dist. (km) to AGS 1.00–1.25	0.007 (0.005)	0.014 (0.009)

(continued on next page)

Table A1 (continued)

	(A)	(B)
Constant	−0.000 (0.001)	0.001 (0.001)
Spatial scale of controls	4-digit zip code	5-digit zip code
Year-by-zip code controls	Yes	Yes
Property characteristics	Yes	Yes
Observations	34,025	25,887
Adjusted R ²	0.723	0.672
F Statistic	2191.1	1070.6

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of homes. The reference categories include distance to nearest attractive green space (AGS) > 1.25 km. Spatially clustered standard errors in parentheses.

*, **, *** Significance at 10%, 5%, and 1%, respectively.

In specific, the models control for fixed effects at the year-by-zip code level. This controls for the possible influence of time-varying spatial processes. Such processes might involve local change in the social or economic composition of a city, see [Livy and Klaiber \(2016\)](#) or [Schwartz et al. \(2006\)](#), which might be correlated with proximity to attractive green space. Essentially, the alternative models compare the prices and characteristics of houses that have sold in the same zip code and in the same year. The resultant findings are similar to our main results. This gives some further assurance that omitted processes are appropriately controlled for in the main models.

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