THE EFFECT OF NATURAL SPACE ON NEARBY PROPERTY PRICES:

ACCOUNTING FOR PERCEIVED ATTRACTIVENESS

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Abstract

This paper estimates the effect of attractive natural space on Dutch residential property prices. We operationalize attractive natural spaces by combining land use data with unique data on the perceived attractiveness of natural spaces. In our main results, the effect of attractive natural space on property prices falls from 16.0% for properties within 0.5 kilometers, to 1.6% for properties up to 7 kilometers away. Our findings advance existing hedonic studies by verifying that economic benefits of living near natural space extend over a larger distances. This has important implications for public policy regarding investment in natural space nearby residential areas. (JEL H41, Q51)

I. INTRODUCTION

It is widely accepted that public natural spaces provide a variety of services which add to the welfare of those who live nearby (Brander and Koetse 2011). This is reflected in property buyers' willingness to pay higher prices for property nearby natural space. As a result, natural spaces are capitalized in surrounding property prices. This capitalization indicates the welfare benefits derived by property buyers who live near to natural spaces. These benefits are moreover essential to decision making, both for conserving or creating natural spaces near residential areas, and to residential development planning at particular distances from – or at the cost of – natural spaces. Worldwide, such decisions are increasingly pressing, given ongoing urbanization (McCann and Acs 2011). It is therefore timely with regard to the private investment decisions of property buyers, as well as public investment for the common good, that empirical studies produce deeper insights into the effect of natural space on nearby property prices (Conway et al. 2010; Gibbons, Mourato, and Resende 2014; Ham et al. 2012; Hoshino and Kuriyama 2010; Melichar and Kaprová 2013; Panduro and Veie 2013). In our estimation of natural space effects on nearby property prices, we focus in particular on the effect of natural spaces that are perceived as *attractive*.

The workhorse for natural space valuation is the hedonic price model. Hedonic models disentangle property prices into implicit marginal prices for property characteristics that also include proximity to natural space. As our point of departure, Palmquist's (2005) review of hedonic modeling techniques emphasizes that, in order to estimate true capitalization in property prices, natural space needs to be measured such that it captures how property buyers *perceive* it. Thus, the appropriateness with which hedonic models reveal property buyers' welfare due to living near natural space, is highly dependent on underlying natural space data. And yet, despite

Palmquist's review, this matter receives little attention in recent hedonic literature. In this paper we address the challenge posed by Palmquist, by measuring the way in which natural spaces are perceived and introducing this measure into a hedonic analysis of property prices.

Most hedonic studies separate natural spaces that are likely to impact differently on property prices only by considering land use data. Land use data allow for the measurement of the distance between transacted properties and natural space of different sizes and types (Conway et al. 2010; Hoshino and Kuriyama 2010; Mansfield et al. 2005; Melichar and Kaprová 2013); but these studies implicitly assume that property buyers evaluate natural spaces with similar land use characteristics as a homogenous good. However, several valuable studies within the rich hedonic literature record higher heterogeneity among natural spaces in land use data due to, among others, differences in noise levels and recreational infrastructure (Ham et al. 2012); landscape diversity and fragmentation (Geoghegan, Wainger, and Bockstael 1997); greenness of vegetation (Bark et al. 2011); and patch configuration (Cho, Poudyal, and Roberts 2008). These measures nevertheless fall back on implicit assumptions about how property buyers perceive natural space. 'Objective' measures seem to be used in the vein of Lancaster's (1966) consumer theory, which is often traced back to the foundations of the hedonic price model (Rosen 1974); this theory asserts that goods themselves possess multiple characteristics from which utility is then derived. Lancaster (1966, 134) elaborates that when operationalizing differences between goods this should capture "the situation in much the same way as the consumer – or even the economist, in private life – would look at it". This then, underlines the importance of perceptions. While the importance of perceptions has been recognized, only a few hedonic studies account for this directly by including subjective evaluations of particular natural land uses (Luttik 2000; Poor et al. 2001).

Luttik’s (2000) empirical investigation of 3,000 Dutch property prices represents the springboard for our study. Its results indicate that natural spaces classified as *attractive* are capitalized in the prices of directly bordering properties, with a rate of up to 12 percentage-points higher than the 4% to 12% rates observed for natural spaces of the same land use type, but which have not been classified as attractive. Luttik’s findings (2000) suggest that measures based on land use data alone lead to inaccurate welfare conclusions, as these are not specific enough to capture natural spaces in the ways that property buyers perceive them (cf. Palmquist 2005). Therefore, in order to *explicitly* classify natural spaces in the way that these are actually perceived, it seems useful to enrich land use data with a measure of perceptions.

Importantly, what matters when perceptions of natural space are used in hedonic analysis is *whose* perceptions are captured in the data. In Luttik (2000), subjective attractiveness is based on Luttik’s own on-site visual inspection of natural land use – which of course is difficult to reproduce. In contrast, the study of Poor et al. (2001) takes the perceptions of property buyers into account; they measure buyers’ subjective evaluations of the water clarity of lakes in close proximity to their properties whose prices are analyzed. The authors find that this subjective measure is outperformed in explaining capitalization in property prices by other measures of water clarity that had been established ‘objectively.’ The reason for this finding, say Poor et al. (2001), is due to individual property buyers’ limited ability to accurately evaluate water clarity. Palmquist’s (2005) review of the hedonic literature suggests that the results of the aforementioned study are flawed because they consider only the winning bidders’ perceptions. This approach is thus inappropriate, since effectively, property prices are determined by the interactions among *all* potential property buyers. Palmquist (2005) recommends that the wider perceptions of all potential property buyers be included in hedonic studies by using aggregated perceptions of residents – measured from survey data – as a proxy for how potential property buyers in general perceive an observed environmental good. That is precisely what we do in this study.

The present analysis contributes to the hedonic literature as the first of its kind to adjust the measurement of natural spaces from land use data, by using data on the way these natural spaces are perceived by residents within the context of a hedonic model. Our results offer important new insights into the welfare that property buyers derive from living nearby natural space, from both an empirical and a public policy perspective. To obtain our results, we have refined conventional measures of natural space in two noteworthy ways.

First, this paper offers a unique method of identifying, from land use data, which of the included natural spaces are perceived as attractive. Until now this type of assessment has not been possible through merely drawing from land use data observed in existing hedonic studies (Ham et al. 2012; Liu et al. 2013; Melichar and Kaprová 2013; Mansfield et al. 2005). Our method combines land use data with survey data that has measured the perceptions - among residents of the Netherlands – on their most attractive Dutch natural spaces. The information obtained, which reflects respondents' preference-ranking for natural space, is aggregated across respondents in order to identify natural spaces that may be perceived as attractive in general. Potential heterogeneity in preference-rankings of natural spaces across individuals is thereby removed. As such, our measure serves as a proxy for those natural spaces, or subareas within contiguous areas of natural spaces of any type, that are perceived as attractive by potential property buyers (c.f. Palmquist 2005). In doing so, we connect the literature on property prices with the field of subjective valuation of nature, within which Hotspotmonitor data has demonstrated its validity in earlier studies (De Vries et al. 2013; Daams and Sijtsma 2013; Sijtsma et al. 2012a, 2012b).

Our second refinement is that we closely analyze the distance decay of the value-added of natural space to property price (Brander and Koetse 2011). In line with most hedonic studies, we focus primarily on estimating capitalization as a result of proximity rather than as a result of view (McConnell and Walls 2005). However, at a later stage we assess the effect of view and incorporate it into our evaluation of the robustness of our main results. Our proximity measure is innovative because it can stretch beyond the nearest natural space(s) in order to identify the distance between a property and precisely the natural space that may add considerable value to the property's price (c.f. Luttik 2000): the nearest natural space perceived as *attractive*. We use this measure to test explicitly for the farthest distance across which attractive natural spaces capitalize in property prices. This approach by itself improves on conventional hedonic studies of natural space, which often use measures with a predetermined, limited, range up to 0.5 kilometers (Waltert and Schläpfer 2010). Such an approach to the measurement of proximity is likely to lead to the underestimation of the economic benefits of living nearby natural space, since in actuality, these may be capitalized in surrounding property prices over distances up to 2 or 3.2 kilometers away (Melichar and Kaprová 2013; Mansfield et al. 2005). We argue that the impact of attractive natural space may increase property prices over an even larger distance, and our unique data allow us to test this hypothesis.

In our analysis we draw from a large sample of approximately 200,000 multiple sales listings in the Netherlands, which also include comprehensive data on locations and property characteristics. We use these data to obtain the capitalization in property prices of attractive natural space. Our estimation derives from within-submarket variation in capitalization, as our specifications control for submarket fixed effects. This approach assumes estimates to be representative across submarkets in our study area, but offers the advantage of observing higher variation in attractive natural space than would be possible to observe from any particular submarket. High variation in attractive natural space, in turn, limits the possible influence of idiosyncratic attractive natural spaces on our analysis. Therefore, the wide spatial scale of our analysis helps to ensure the potential validity of the perceived attractiveness-based measurement approach that we introduce in this paper, although there may of course be some trade-off between the spatial representativeness and the precision of estimates. In order to evaluate the robustness of our main results, we estimate several alternative specifications. In addition, we explore if the capitalization of proximity to attractive natural space in property prices varies at the regional scale in accordance with levels of urbanization.

We structure the remainder of the paper as follows. The next section describes how we identify attractive natural spaces. The study area and natural space-related data are then discussed in section III, followed by a description of the estimation data in section IV. Empirical models are formulated in section V. Results are presented and elaborated in section VI, and section VII provides a concluding discussion.

II. IDENTIFYING ATTRACTIVE NATURAL SPACES

We identify specific natural spaces that residents of our study area perceive as attractive among the natural spaces observed in land use data. To achieve this, we combine land use data with value mapping survey data. Value mapping is a spatially explicit procedure where respondents mark natural spaces that they associate with the investigated social value on a (digital) map; these designated point–locations are then saved in XY-coordinates (Brown and Reed 2012;

Brown and Kyttä 2014). With these data we are able to identify *locally coherent* attractive natural spaces. No a priori assumptions are required about what mix of land use characteristics makes a natural space coherent. Coherency arises from the accumulation of our spatially-precise survey data, from which we identify clusters that we next overlay with land use data. The stepwise procedure is described below.

The first step (Figure 1a) is to measure the density of marked point–locations, hereafter referred to as 'markers' which indicate attractive natural spaces across our study area. We do this on a 250x250 meter raster grid. For each grid cell, the number of markers per square kilometer within a 1,250 meter search radius is measured. The length of the search radius impacts the identified density of markers *surrounding* a grid cell. The density of markers may or may not exceed a certain clustering threshold, which we duly apply in the next step, as an indicator of attractive natural space. It is relevant to our study that a higher search radius decreases the weight of markers relatively nearby the grid cell in the measured density; in that case attractive natural spaces are smoothed out 'in space' into fewer and larger areas, and vice versa (see Appendix for a substantiation of the 1,250 meter search radius applied in this study).

In the second step (Figure 1b), for those neighboring grid cells with a marker density that equals or exceeds a predefined cut-off value, we merge these into clusters. In this way we extend a similar technique used in a different context (not property price) of a value mapping study by De Vries et al. (2013), who use a cut-off value based on visual inspection of a few tens of resulting clusters. Different from the De Vries et al. (2013) study, we substantiate our choice for a cut-off value by following the rationale of the Hotspotindex (Sijtsma et al. 2012b). Our cut-off value equals the density of markers observed when markers are evenly distributed across our study area – the hypothetical case where no clustering is present. We merge neighboring grid cells with a density above the cut-off value into clusters, and in so doing identify clusters across our study area in a consistent way. To secure the fit of clusters on the markers from which they arise, we keep only the clusters that depend on multiple value mapping of survey respondent perceptions, as well as clusters that include at least as many markers as they would if they were distributed evenly across the study area. The remaining clusters represent *attractive* natural spaces in accordance with the aggregated perception of residents as derived from the observed value mapping data.

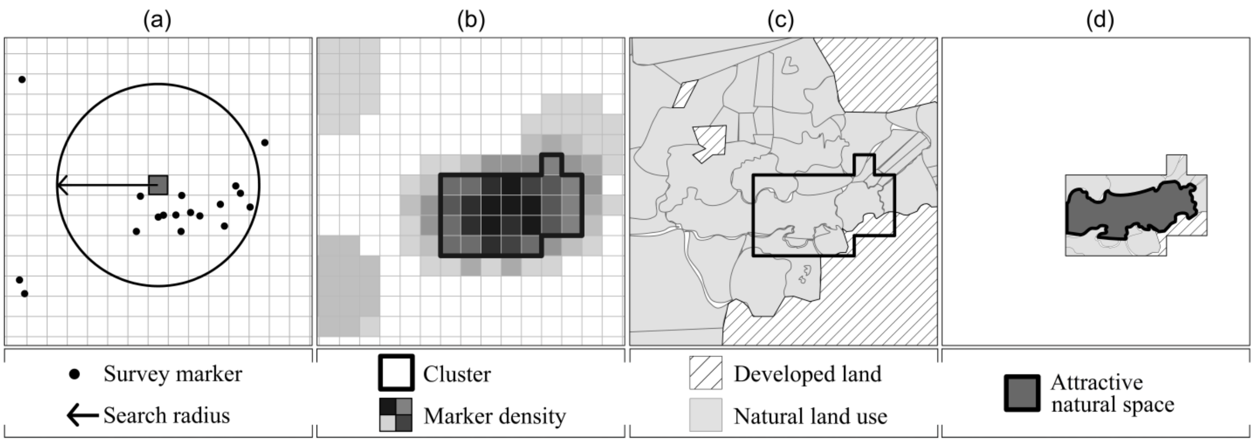

Figure 1. Schematic visualization of how we identify attractive natural spaces. (a) Shows the search radius within which the average density of value mapping survey markers per square kilometer is measured. The measured density is captured in the highlighted grid cell. Grid cells with varying marker density values are shown in (b). Density values that exceed a predefined cut-off value are delineated with thick borders, thus indicating a cluster. An overlay of clusters with land use data is then made (c). In (d) we keep only the natural spaces that include multiple value mapping markers in order to ensure consistent measurement of attractive natural spaces.

In the third, and final step (Figures 1c and 1d), we acknowledge that the form of the remaining clusters may deviate slightly from the precise borders of included natural spaces and, as a result, show a small degree of overlap with developed land. This is because the search radius used in clustering markers also determines the distance between the borders of clusters and the included markers. Moreover, the grid cells, in which marker densities are captured to indicate attractive natural spaces, are quadrangle shaped. To resolve these minor issues of spatial form, we perform an overlay of clusters with land use data (Figure 1c). After this adjustment, the outer borders of natural spaces indicated as attractive follow precisely the shape of the natural spaces which it comprises. For added security (Figure 1d), we keep all comprised natural spaces containing more than one marker inside their own land use borders. In this way we can minimize the influence of relatively isolated markers at the outer boundaries of the spatial form of attractive natural spaces. The procedure described above essentially depicts coherent natural spaces that we assume the surveyed residents to have perceived as *attractive* in general.

III. STUDY AREA AND NATURAL SPACE-RELATED DATA

The highly urbanized Netherlands has a slowly rising population of 16.8 million people. Its land surface is approximately 35,000 square kilometers (Statistics Netherlands 2013).[1] Residential areas are typically compact, mainly as a result of strict land use planning controls implemented by the Dutch government during the second half of the 20th century up to the present day. This 'compactness' is illustrated by data from Statistics Netherlands showing the Netherlands to have an average population per square kilometer of 473, when all land is taken into account, with 17% of this land as actually developed. Due to their compact form, residential areas are typically in close proximity to natural space. Natural space – including agricultural areas – comprises 83% of the country's land surface in 2010. Dutch natural spaces are predominantly either public goods or they provide public benefits.

Land use data for 2010 have been acquired from Statistics Netherlands (CBS). All natural spaces of at least one hectare in size are included, except for the North Sea's surface, which we digitize from an ESRI imagery basemap (Figure 2a). We define *natural space* as all types of natural land use within the land use dataset, with the exception of sludge fields. Specifically, natural space includes parks and recreation areas, forests, open dry nature, open wet nature, coastal water bodies, inland water bodies, and agricultural areas. Our definition also allows for agricultural areas because, although they are cultivated lands, some agricultural areas may nevertheless be evaluated as attractive natural spaces by property buyers.

Using the method set out in section II, attractive natural spaces in our land use data are derived from value mapping survey data from the Hotspotmonitor (HSM) database. In the HSM-survey, respondents were asked to mark attractive natural spaces that may be on land or water, inside or outside urban areas, and which also satisfy the condition that 'nature' be featured in a broad sense and be perceived as *attractive* – for respondents' subjective reasons.[2] As such, each HSM marker reflects a holistic subjective evaluation that pertains to the designated natural space. Markers can be placed with high precision, as the HSM-survey uses the Google Maps interface. The Google Maps interface allows respondents to adjust zoom levels and pan smoothly across a map when searching for an attractive natural space to mark. We use markers from the Hotspotmonitor database that have been placed on nature at the national level. At this scale, HSM respondents can use a single marker to designate *any* of the natural spaces in our study area as the most attractive.[3] Therefore, natural spaces perceived as (highly) attractive can be identified consistently across the study area. As mentioned above, national markers from the HSM database have been analyzed in several studies outside the field of property prices, including Sijtsma et al. (2012a; 2012b; 2014), De Vries et al. (2013), and Daams and Sijtsma (2013).

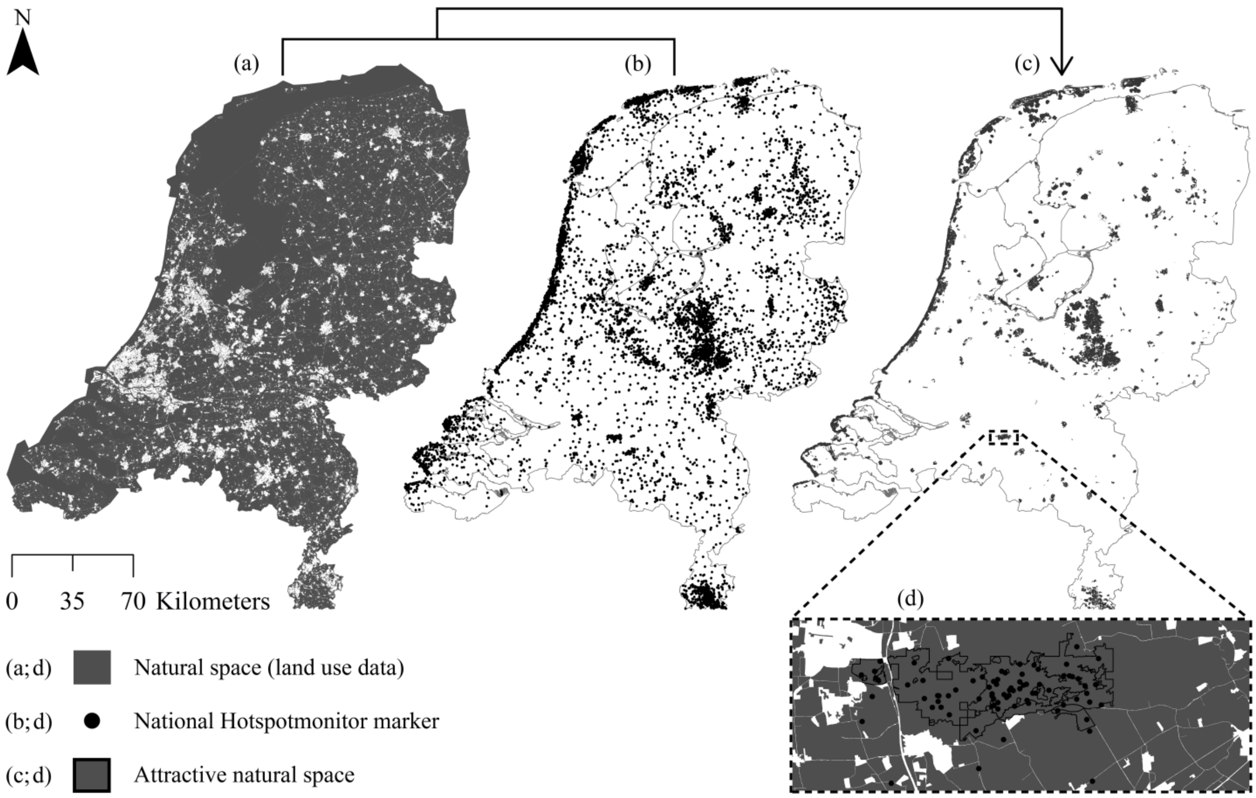

Figure 2. The areas of all natural spaces observed in our land use data (a) sum to 35,583 square kilometers. 6.83% of this area is covered by attractive (PA) natural spaces (c). Note that, for PA natural spaces, N=385 due to the presence of many relatively small PA natural spaces. The median size of a PA natural space is 157 hectares. PA natural spaces are identified by combining (a) land use data with (b) Hotspotmonitor value mapping survey data. (d) shows a zoom-in view of an individual PA natural space, along with the value mapping and land use data.

Our sample consists of 8,613 national markers within Dutch municipal borders (Figure 2b).[4] The markers are derived from all HSM datasets available as of November 2013, and the earliest among these datasets originates from 2010. Over 80% of these markers are placed by respondents to stratified surveys. Respondents across the Netherlands were selected from the GfK internet-panel, the most spatially comprehensive internet panel in the Netherlands, which also samples and accounts for socio-economic representativeness. Respondents are sampled from areas spread across our study area.[5] We use the full HSM sample for identifying attractive natural spaces in our land use data.

Attractive natural spaces account for 6.83% of the total area of natural spaces in our land use data. Table 1 gives descriptive statistics for the areas of (attractive) natural spaces within our study area when disaggregated by type of natural space. Importantly, our data also show that for each distinct type of natural space, 40%-95% of its total area is within attractive natural space that includes multiple natural space-types within its borders. The implication here is that disaggregation of attractive natural spaces by distinct types would be a misspecification of the way these are perceived. In our main analysis we will therefore consider attractive natural spaces as spatial units that may contain any mix of natural space types that are *locally coherent*.

Table 1. Share per distinct natural space type within the total areas of all natural space and attractive (PA) natural space.

Type	All natural space	Attractive natural space
	Share (%)	Share (%)
Parks and recreational areas	1.1	0.6
Agricultural land	63.2	14.3
Forest	9.7	31.5
Open dry nature	2.5	18.2
Open wet nature	1.5	3.6
Coastal water	10.3	20.4
Inland water	11.8	11.4

Note: The distinguished types are those that are present in our land use data.

IV. ESTIMATION DATA

The property observations in our dataset cover 293,621 sales of single-family properties throughout the Netherlands from January 2009 to December 2012. These data were obtained from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM). The NVMs database is a record of approximately 80% of the total transactions on the Dutch market in the observed years. These data have been applied in several property hedonic studies, for example Liu (2013), and Van Ommeren, Wentink, and Dekkers (2011).

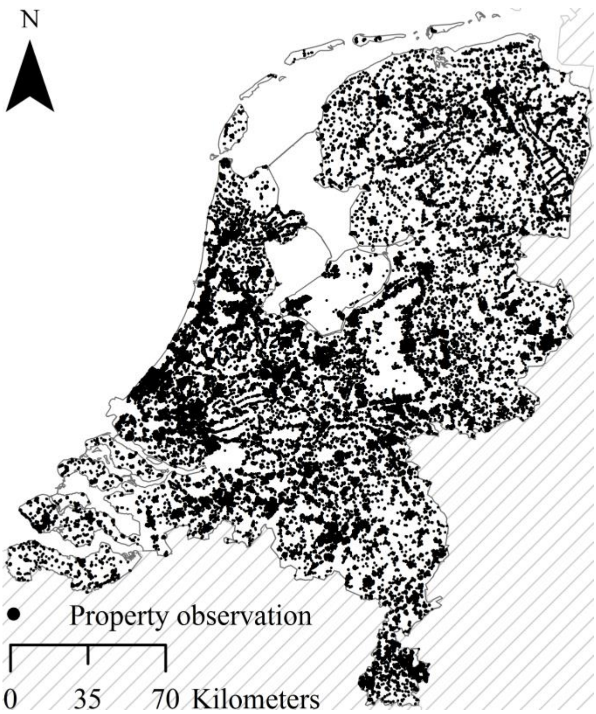

Figure 3. The locations of properties in our estimation sample (N=203,344).

Property characteristics described by the data include transaction price and date as well as a number of structural characteristics: living area, parcel size, number of rooms, period of construction, type of heating, type of structure, and presence of insulation materials. The data also indicate the NVM brokers' local property market (N=76) within which a property is located. Our data include zip codes and house numbers that allow us to geocode the dataset at the address level. Address-level coordinates are derived from the Registers for Addresses and Buildings (BAG) and are maintained by the Netherlands Cadastre, Land Registry and Mapping Agency.

Using these address locations we are able to capture each property's Euclidean distance to the nearest natural space perceived as *attractive* – hereafter known as *perceived attractive* (PA) natural space. We observe that properties' mean distance to PA natural space is 4.63 kilometers.[6] We discretize this measure of nearest distance by following Liu et al. (2013) and Mansfield et al. (2005) at the distance intervals reported in Table 2.

Furthermore, since property buyers may, in addition to distance, also consider the quantity of PA natural space surrounding listed property for sale in their purchase decision, we construct a measure to evaluate quantity. This measure captures the share of land comprised of PA natural space within 7 kilometer rings surrounding the transacted properties. The radius of these rings is specified at the maximum distance across which initial regressions have consistently indicated that the nearest attractive natural spaces capitalize in property prices (Table A2, Appendix). Within the same 7 kilometer rings we also measure the share of land comprised of less attractive (non-PA) natural space. As a result, the reference category for our ring-based measure is developed land.

Finally, we enrich our property data with two additional location measures. The first is a measure based on the density of addresses surrounding each property, signifying: urban, intermediate, or non-urban location. These degrees of local urbanization are, in the case of the Netherlands, best reflected by a fine-scale spatial definition rather than, e.g., the NUTS-3 level-based OECD definition, due to its sharp rural-urban divides in the built environment (Delfmann, et al. 2014). So, by following the definitions of degrees of local urbanization used by Delfmann et al. (2014) and Statistics Netherlands, we generate three dummy variables: urban (address density >= 1500); intermediate (500=< address density <1500); and non-urban (address density < 500) locations. These data of Statistics Netherlands include the 2011 density of residential and non-residential addresses per square kilometer within a 1 kilometer radius, averaged out at the 500x500m grid cell level.

Our second additional measure of location incorporates the notion of Visser, Van Dam, and Hooimeijer (2008) that number of jobs within commuting distance is important in the explanation of variation in Dutch property prices. While such a measure is typically associated with local urbanization, which we proxy with mean address density, we notice that rural-urban economic tie-ins through commuting flows render these measures complementary (Daams and Sijtsma 2013). Using LISA 2011 Dutch employment data geocoded at address level, we measure the number of jobs within 14.6 Euclidean kilometers from the transacted properties, i.e., the 2005 mean Euclidean commuting distance observed by Statistics Netherlands. After cleaning our dataset, the estimation sample contains 203,344 observations with full information on our study variables.[7] Descriptive statistics for the variables are provided in Table 2, and Figure 3 shows locations of the observed properties.

Table 2. Descriptive statistics for the estimation sample (N=203,344).

Variable	Mean	Std. Dev.
Price (€)	*€ 263,149*	*€ 136,843*
Living area (m²)	*128.70*	*36.83*
<105	0.24	
>=105 & =<142	0.51	
>142	0.25	
Number of rooms	*4.99*	*1.19*
<5	0.32	
5	0.43	
>5	0.25	
Constructed before 1945	0.20	
Constructed between 1945 and 1980	0.42	
Constructed after 1980	0.38	
Parcel size (m²)	*643.75*	*13,530.71*
<140	0.24	

Table 2 continued		
>=140 & =<300	0.50	
>300	0.26	
Central heating	0.94	
Duplex house	0.03	
End-of-terrace house	0.19	
Semi-detached house	0.20	
Detached house	0.15	
Terraced house	0.43	
Insulation	0.43	
Transaction in quarter 1	0.23	
Transaction in quarter 2	0.26	
Transaction in quarter 3	0.24	
Transaction in quarter 4	0.28	
Year of transaction 2009	0.25	
Year of transaction 2010	0.26	
Year of transaction 2011	0.24	
Year of transaction 2012	0.25	
Jobs within commuting distance (x1,000)	*240.04*	*179.81*
Address density	*1,402.91*	*954.58*
Urban location	0.39	
Intermediate location	0.45	
Non-urban location	0.16	
Distance (km) to nearest attractive (PA) natural space	*4.63*	*3.55*
0-0.5km	0.05	
0.5-1km	0.07	
1-2km	0.16	
2-3km	0.14	
3-4km	0.11	
4-5km	0.09	
5-6km	0.08	
6-7km	0.07	
7-8km	0.06	
>8km	0.17	
% PA natural space in 7km ring	*4.62*	*6.92*
% Non-PA natural space in 7km ring	*68.09*	*14.97*
% Developed land in 7km ring	*27.29*	*13.44*

Notes: For % Non-PA natural space in 7km ring we observe min.=20.68 and max.=98.28; for % PA natural space in 7km ring we observe min.=0 and max.=68.65; and for % Developed land in 7km ring we observe min.=0.78 and max.=74.57. Ratio variables are in *italics*.

V. EMPIRICAL MODELS

Baseline specification

The specification of the basic hedonic price model (1)[8] for property *i* (i=1,...,n) in submarket *s* (s=1,…,S) at time *t* is

$$\ln P_{ist} = \alpha + \sum_{a=1}^{A} \beta_a \mathbf{X}_{ista} + \varepsilon_{ist}\,, \qquad [1]$$

where α is the constant; ln P_{ist} the natural log of the selling price; $\mathbf{X}_{ista}$ the *a* th relevant property characteristic (a=1,…,A) including location and time fixed effects; and ε_{ist} denotes spatially clustered standard errors. We use a semilog functional form because the transaction data have a right-side tail.

The selection of variables for this analysis follows the conventional hedonic approach described by Malpezzi (2003). Observed property characteristics are: size of living area, number of rooms, parcel size, type of heating, and type of structure. Degree of local urbanization and number of jobs within mean commuting distance from property *i* are also included.

Property prices may be based on prices of similar properties nearby. We control for spatial dependence of property prices using submarket fixed effects (N=76). The observed submarkets are regions that have been designated by professional members of the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) to contain areas with high substitutability of properties. Bourassa, Cantoni, and Hoesli (2007) find that similar experience-based submarket fixed effect models explain variation in property prices better than models which explicitly formalize the spatial structure of errors. Nevertheless, since unobserved property characteristics may be correlated across properties below submarket scale due to similarity in structural characteristics or locational amenities, spatial error dependence should be accounted for (Liu 2013). We therefore follow Heintzelman and Tuttle (2012), by including fixed effects while also allowing for clustered standard errors at street-level, six-digit zip codes.

Main perceived attractiveness specification

We now turn to model (2), which includes unique measures of proximity to *perceived attractive* (PA) natural spaces. PA natural spaces are those natural spaces that residents may perceive as attractive in general. A strength of this measure is that it is drawn from a sample of survey respondents independent of the subset of the population that has bought or sold properties. The specification of model (2) is expressed as

$$\ln P_{ist} = \alpha + \sum_{a=1}^{A} \beta_a \mathbf{X}_{ista} + \sum_{c=1}^{C} \beta_c \mathbf{Dist\ PA}_{\ istc} + \sum_{d=1}^{D} \beta_d\ \mathbf{Ring\ 7km}_{istd} + \varepsilon_{ist}, \qquad [2]$$

where **Dist PA**$_{istc}$ is the vector of dummy variables indicating whether the Euclidean distance between property *i* and the nearest PA natural space falls within interval *c* (c =0-0.5km, 0.5-1km, 1-2km, 2-3km, 3-4km, 4-5km, 5-6km, 6-7km, 7-8km); and **Ring 7km**$_{istd}$ is the vector of two control variables that capture the percentage shares of land cover of PA and less attractive (non-PA) natural spaces within a 7 kilometer ring surrounding property *i*.

Model (2) allows us to test for distance decay in the effect on property prices which earlier empirical studies have led us to expect (Brander and Koetse 2011; Mansfield et al. 2005; Melichar and Kaprová 2013). These effects are allowed to be non-linear across space. We expect the distance over which attractive (PA) natural spaces to have an impact on property prices to be wider than the maximum 3.2 kilometers – across which effects are reported in existing studies (Mansfield et al. 2005) – because those studies do not account for perceived attractiveness. With regard to the ring-based control variables, we expect their price-effects to be positive for a marginal increase in PA natural space, and negative for a similar increase in non-PA natural space, since the reference class for these variables is developed land.

VI. EMPIRICAL RESULTS

Baseline specification results

Table 3 reports the results for our two model specifications. The models indicate joint significance for both specifications. Let us first consider the results for baseline model (1) without measures of proximity to natural space. Most of the estimates are as expected. Premiums on property prices are found for larger properties in terms of number of rooms, living area, and parcel size. The presence of central heating and insulation material is also valued positively by property buyers. Type of structure matters too, as detached properties have higher market values than other property types. However, one surprising finding is that urban location is associated with lower property prices compared to non-urban and intermediate locations. We suggest that this is due to the fact that the model also controls for jobs within mean commuting distance. The coefficient for jobs within mean commuting distance indicates a strong effect on property prices; in addition, this variable correlates higher with the measure of urban location than for the non-urban and intermediate location measures. Furthermore, consistent with Liu's (2013) study of Dutch property prices, we find that properties constructed between 1906 and 1945, or after 1980, sell at higher prices than properties built between 1945 and 1980.

Main perceived attractiveness specification results

Model (2) in Table 3 provides the results for the main specification that includes measures of proximity to natural spaces that residents of our study area may perceive as attractive (PA) in

Table 3. Regression results of property hedonic models.

	(1)	(2)
Nearest PA within 0-0.5km		0.149*** (0.00450)
Nearest PA within 0.5-1km		0.101*** (0.00383)
Nearest PA within 1-2km		0.0842*** (0.00300)
Nearest PA within 2-3km		0.0610*** (0.00287)
Nearest PA within 3-4km		0.0366*** (0.00287)
Nearest PA within 4-5km		0.0347*** (0.00270)
Nearest PA within 5-6km		0.0293*** (0.00273)
Nearest PA within 6-7km		0.0159*** (0.00280)
Nearest PA within 7-8km		0.00188 (0.00281)
% PA in 7km ring		0.00222*** (0.000191)
% Non-PA in 7km ring		-0.00205*** (0.000104)
Living area <105m²	-0.164*** (0.00148)	-0.164*** (0.00146)
Living area >142m²	0.252*** (0.00177)	0.247*** (0.00172)
Number of rooms <5	-0.0377*** (0.00126)	-0.0389*** (0.00124)
Number of rooms >5	0.0701*** (0.00148)	0.0675*** (0.00144)
Constructed before 1945	0.0898*** (0.00220)	0.0776*** (0.00212)
Constructed after 1980	0.0844*** (0.00151)	0.0900*** (0.00149)
Parcel size <140m²	-0.0775*** (0.00155)	-0.0762*** (0.00151)
Parcel size >300m²	0.182*** (0.00210)	0.177*** (0.00206)
Central heating	0.113*** (0.00286)	0.112*** (0.00283)
Duplex house	0.133*** (0.00332)	0.135*** (0.00324)
End-of-terrace house	0.0295*** (0.00135)	0.0312*** (0.00132)
Semi-detached house	0.149*** (0.00185)	0.150*** (0.00181)
Detached house	0.334*** (0.00301)	0.338*** (0.00295)
Insulation	0.0508*** (0.00132)	0.0564*** (0.00129)
Jobs within commuting distance (x1,000)	0.0491*** (0.00228)	0.0461*** (0.00235)
Urban location	-0.00766*** (0.00227)	-0.0156*** (0.00231)
Intermediate location	0.00966*** (0.00203)	0.00635*** (0.00201)
Constant	11.24*** (0.0152)	11.43*** (0.0192)
Observations	203,344	203,344
R-squared	0.738	0.749
F statistic	3149	2950
Root MSE	0.218	0.214

Notes: Dependent variable is the natural log of transaction price. The reference categories include distance >8km to nearest attractive (PA) natural space; living area of 105-142 m^2; number of rooms equals 5; construction between 1905-1945; parcel area of 140-300 m^2; row house; non-urban location. Both models include fixed effects for year, quarter and spatial submarket. Specification (1) includes the baseline specification. Specification (2) includes the main perceived attractiveness specification. Clustered standard errors (ZIP6) are in parentheses.
***, **, * Indicate significance at 1%, 5% and 10%, respectively.

general. Let us now examine the effect of distance to the nearest PA natural space on property prices. We estimate this effect for discrete distance-intervals using dummy variables. Thus, given the model specification's semi-log functional form (Halvorsen and Palmquist 1980), the associated coefficients can be interpreted as a percentage change in property price after a $(e^{\beta} - 1)$ transformation. The percentage of the effect on property price, given a property's distance to the nearest PA natural space, is shown in Figure 4. The price-effects are relative to the prices of properties located 8 kilometers, or farther, away from PA natural space. For properties within 0.5 kilometers from PA natural space, we find a 16.0% price-effect (Figure 4). This finding is similar to Luttik (2000) in her study on prices of properties bordering directly on natural space which she evaluates as attractive. Importantly, beyond a distance of 0.5 kilometer, the effect falls to 1.6% for a 6 to 7 kilometer distance. Our estimates clearly show distance decay, as price-effects fall smoothly over the 0-7 kilometer range. We find no significant price-effect for properties 7 to 8 kilometers away from PA natural space: this finding indicates that PA natural spaces do not capitalize in the prices of properties more than 7 kilometers away. The finding of distance decay as such is consistent with results from earlier empirical studies reviewed by Brander and Koetse (2011). Until now, the distance across which our results indicate the presence of distance decay had not been verified, thus confirming the value of an approach that incorporates the perceived attractiveness of natural spaces.

Model (2) also evaluates if, in addition to the effects of the nearest PA natural space, there are effects associated with the share of land cover of PA and non-PA natural spaces within 7 kilometers of properties. The associated coefficients show an additional 0.22% effect on property prices for a marginal increase in the share of land cover of PA natural space, at the cost of developed land, the reference category for share of land cover.[9]

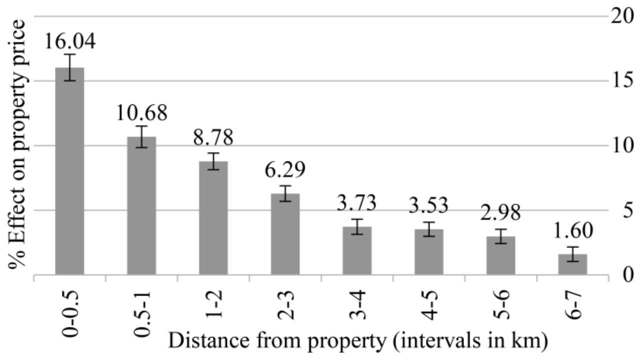

Figure 4. Percentage effect of nearest attractive (PA) natural space on property price by distance to the property, after $(e^{\beta} - 1)$ transformation of model (2) coefficients. Error bars give each price-effect's 95% confidence interval.

In contrast to this result, the coefficient for the share of land cover of non-PA natural space within a 7 kilometer ring indicates a -0.21% effect on property prices. The effect being negative signifies that property buyers attach positive value to a marginal decrease in non-PA natural space – which also includes agricultural land – in exchange for a proportional increase in developed land. This finding is in line with people's strong overall preference for living nearby urban amenities that may correlate with the amount of nearby developed land (Storper and Scott 2009). A Wald test comparing the coefficients for the shares of PA and non-PA natural space rejects the hypothesis that these coefficients are equal (the *F*-statistic is 589.26). In order to evaluate the overall robustness of model (2), we next carry out estimates on several alternative specifications.

Robustness checks

Concerns could arise with respect to the spatial scale of the submarket fixed effects (N=76). If these are too large, they may not be sufficient controls for omitted variable bias (Anderson and West 2006). We thus re-estimate model (2) in specification (3) to include fixed effects at the fine scale of four-digit zip codes (ZIP4; N=3,255), which are comparable to U.S. census tracts. In so doing we constrain the effect of the nearest attractive (PA) natural space on property prices to a variation within the scope of ZIP4 areas. Results are presented in Table 4.

Model (3) results differ from model (2) in two main ways. First, most of the nearest distance effects in model (3) are somewhat lower than effects found in model (2). Second, in model (3), the coefficient for the share in land cover of PA natural space within a 7 kilometer ring has a negative sign. Both differences indicate that ZIP4 fixed effects absorb some variation in nearby property prices which, in the case of submarket fixed effects, was allowed to be explained through proximity to PA natural space (Abbott and Klaiber 2010). However, proximity effects are likely to have been underestimated in model (3), in particular those estimated using the measures of the share of (attractive) natural space within a 7 kilometer ring. This is due to the fixed-effect scale: keep in mind that the largest ZIP4 area in the Netherlands encompasses 13,662 hectares, which is smaller than the 15,393 hectare area of a 7 kilometer ring. An important finding is that, even when tight controls for omitted variable bias are used, the distance across which the nearest PA natural spaces capitalize in property prices is consistent with the 7 kilometers identified in model (2).[10]

We also investigate the sensitivity of estimates in model (2) for non-representativeness of the Hotspotmonitor value mapping data due to slight oversampling of respondents in Amsterdam. Model (4) excludes observations of property transactions in Amsterdam. The resulting estimates are similar to those generated using the full estimation sample of property transactions.

The reader will recall that we also need to consider the role of views. The measures of proximity in model (2) may yield inaccurate estimates of effects on property prices because view

Table 4. Regression results, alternative model specifications 3–6.

	(3)	(4)	(5)	(6)
Nearest PA within 0-0.5km	0.118*** (0.00797)	0.146*** (0.00454)	0.137*** (0.00451)	0.144*** (0.00449)
Nearest PA within 0.5-1km	0.0804*** (0.00764)	0.0991*** (0.00386)	0.0987*** (0.00383)	0.0971*** (0.00384)
Nearest PA within 1-2km	0.0600*** (0.00729)	0.0836*** (0.00302)	0.0824*** (0.00300)	0.0812*** (0.00302)
Nearest PA within 2-3km	0.0548*** (0.00696)	0.0621*** (0.00288)	0.0596*** (0.00287)	0.0586*** (0.00288)
Nearest PA within 3-4km	0.0459*** (0.00655)	0.0378*** (0.00287)	0.0354*** (0.00287)	0.0321*** (0.00287)
Nearest PA within 4-5km	0.0352*** (0.00601)	0.0350*** (0.00270)	0.0339*** (0.00270)	0.0284*** (0.00270)
Nearest PA within 5-6km	0.0253*** (0.00543)	0.0294*** (0.00273)	0.0285*** (0.00273)	0.0226*** (0.00274)
Nearest PA within 6-7km	0.0236*** (0.00470)	0.0160*** (0.00280)	0.0153*** (0.00280)	0.0107*** (0.00280)
Nearest PA within 7-8km	0.00480 (0.00369)	0.00224 (0.00281)	0.00160 (0.00281)	-0.00257 (0.00282)
% PA in 7km ring	-0.00165*** (0.000559)	0.00247*** (0.000192)	0.00219*** (0.000190)	0.00129*** (0.000197)
% Non- PA in 7km ring	-0.00250*** (0.000350)	-0.00192*** (0.000105)	-0.00206*** (0.000104)	-0.00187*** (0.000107)
View on PA			0.0720*** (0.00615)	
Dist. (km) to non-PA park/recreation area				-0.00696*** (0.00110)
Dist. (km) to non-PA coastal water				-0.000450*** (0.000121)
Dist. (km) to non-PA inland water				0.00515*** (0.00152)
Dist. (km) to non-PA forest				-0.00711*** (0.00106)
Dist. (km) to non-PA agricultural land				0.00243 (0.00246)
Dist. (km) to non-PA open dry nature				-0.00377*** (0.000262)
Dist. (km) to non-PA open wet nature				0.00681*** (0.000473)
Constant	13.28*** (0.195)	11.42*** (0.0192)	11.43*** (0.0191)	11.41*** (0.0196)
Controls (17)	Yes	Yes	Yes	Yes
Observations	203,344	201,120	203,344	203,344
R-squared	0.818	0.747	0.749	0.750
F statistic	272.9	2921	2930	2798
Root MSE	0.183	0.214	0.214	0.213

Notes: See Table 3. Dependent variable is the natural log of transaction price. Specification (3) includes fixed effects for ZIP4 areas; standard errors are not clustered in this specification because when errors are clustered (at ZIP6 level), regression analysis yields similar results but no F value, although degrees of freedom seem sufficient. Specification (4) excludes observations located in the Amsterdam submarket. Specification (5) includes a proxy for view, and specification (6) includes measures of distance to nearest non-PA natural spaces of distinct land use types. Clustered standard errors (ZIP6) are in parentheses. *** Indicates significance at 1%.

is not controlled for – as shown for measures of 0.2 kilometer proximity in the Walls, Kousky, and Chu (2015) study on the value of views. We expect this to be a low-distance issue, as found by Cavailhès et al. (2009), who used comprehensive measures to test how view-effects vary with distance. Their results indicate no significant view-effects beyond 0.3 kilometer. Although we do not have comprehensive measures for view similar to those used in view-specific hedonic studies, we can use a comprehensive *proxy* for view in our robustness check. In specifying this proxy measure for view on PA natural space, we consider that our study area is practically flat and highly urbanized, and buildings are therefore the main obstruction to view. Hence, *view* is indicated when a straight line between a transacted property and the nearest PA natural space border is not broken by one of the 11.5 million buildings (of any structural type, e.g., houses, barns, offices) in our study area.[11] Model (5) results verify that these properties sell at a significant premium. Compared to results in model (2), the inclusion of a proxy variable for view on PA natural space does somewhat lower the size of the coefficient for property 0 to 0.5 kilometer away from PA natural space, from 0.149 to 0.137.[12] It is important to mention that the proximity-effects beyond 0.5 kilometer, our main concern in this study, maintain robustness with this change in specification.

Another consideration is the sensitivity of estimates in model (2) for controlling for proximity to non-PA natural spaces of distinct nature-types that are found to relate to property prices (McConnell and Walls 2005). Varying in accordance with nature-type, and by excluding coastal water because it is relatively peripheral, 44%-95% of the observed properties are closer to a non-PA natural space of a particular nature-type than to (any) PA natural space. To evaluate if this influences our main results, we estimate model (6), which controls for the distances between properties and non-PA natural spaces of the seven distinct types in our land use data. It is noteworthy that the coefficients for each of the non-PA natural space types are not directly comparable to findings in existing hedonic studies, since they do not account for natural spaces being (non)attractive.[13] Importantly, the estimates in model (6) for proximity to PA natural space are highly similar to those in model (2), so we can indeed confirm the validity of our measure of PA natural spaces.

Furthermore, aftershocks of the global financial crisis beginning in the latter part of 2007 have in general impacted on the disposable income of property buyers, and these might also have influenced their willingness-to-pay for living nearby PA natural space (Liebe, Preisendörfer, and Meyerhoff 2010). To test whether this is the case, we partition our dataset by year of property transaction and re-estimate model (2) on the resultant four subsamples. Observations of property transactions in 2009, 2010, 2011, and 2012 are thus included in separate models. Estimates of these models indicate that model (2) estimates of PA natural space effects on nearby property prices are very robust for the year of transaction – hence these models' results are not presented here.[14] The implication of these findings is that aftershocks of the financial crisis do not seem to have influenced PA natural spaces capitalization in property price – thereby confirming the robustness of our main results.

Exploring regional variation in the price-effect

After having established the robustness of the main perceived attractiveness specification in our analysis, in this empirical extension we check for regional variation in PA natural space effects on property prices. Specifically, we test whether effects vary in accordance with regional level of urbanization. This focus is in response to Brander and Koetse's (2011) meta-analysis of property hedonic studies, which asserts that with regard to regional characteristics, mainly level of urbanization of the observed study area has a considerable positive relation with the size of reported price-effects from natural space. Brander and Koetse suggest that this positive relation may arise from natural space being scarcer in regions with higher levels of urbanization.[15] We also explore if this mechanism is pertinent to our study area.

To distinguish between *coherent urban* regions, we use 2013 data from the OECD on so-called Functional Urban Areas (FUAs). FUAs contain urban areas and their hinterlands which are identified through the use of fine-scale population densities and commuting flows (OECD 2012). These data allow us to distinguish between *metropolitan* regions (population > 500,000); *urban* regions (population < 500,000); and *non-urban* regions situated outside FUAs. This definition is visualized in Figure 5. On the basis of the three aforementioned levels of regional urbanization, we partition our dataset of property transactions and re-estimate model (3), as it includes ZIP4 fixed effects. ZIP4 fixed effects control for unobserved spatial factors below regional level, and prevent such factors from becoming more pronounced as we narrow the extent of our study area.

The results for models (7), (8), and (9) estimated for observations within metropolitan, urban, and non-urban regions, respectively, show that the PA natural space effect on nearby property prices varies with regional level of urbanization in two main ways. First, at any distance interval the price effect is relatively higher in metropolitan and urban regions compared to non-urban regions. This result is in line with the meta-analysis carried out by Brander and Koetse (2011), who suggest that this may be due to higher scarcity of natural space in the more urbanized regions. This explanation seems applicable to our findings, as *metropolitan*, *urban*, and *non-urban* regions contain 12.27%, 36.58%, and 51.15%, respectively, of the area of land-based PA natural spaces in our study area. However, what the notion of scarcity does not explain is that we find relatively high price effects for the urban subsample compared to the metropolitan

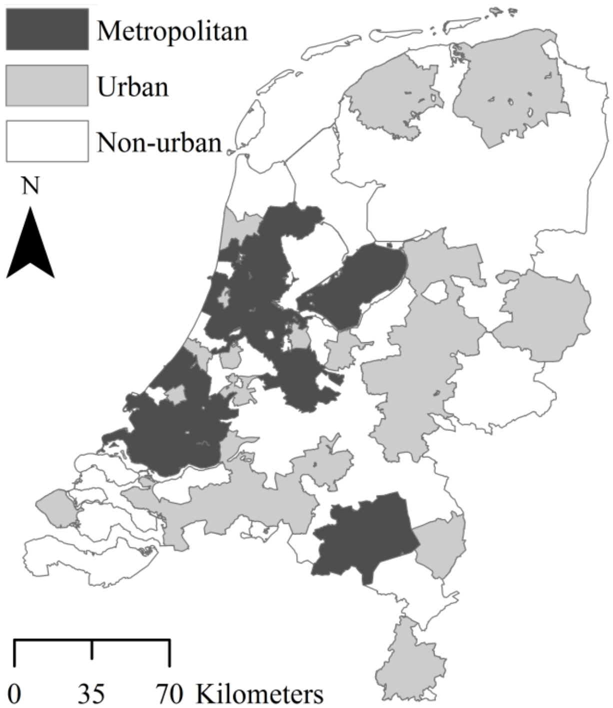

Figure 5. Regions by degree of urbanization, based on functional urban areas.

subsample. A possible explanation is rooted in the extensive regional economic literature, which affirms that, in evaluations of alternative residential locations, people balance their preferences for nearness to urban amenities, such as employment opportunities, and proximity to attractive natural space amenities (Partridge 2010). The preferred balance may, for buyers in a metropolitan region, tip toward urban amenities rather than natural space amenities, in line with Storper and Scott (2009). However, it is noteworthy that, compared to buyers in *metropolitan* regions, buyers in *urban* regions may bid relatively high prices for properties nearby PA natural space, as they may prefer to live close to the best of both worlds: urban amenities *and* attractive natural space amenities.

The second main way in which PA natural space effects on property prices vary across models (7), (8), and (9) pertains to the distance across which estimates of effects on property

Table 5. Regression results, alternative model specifications 7–9.

	(7)	(8)	(9)
Nearest PA within 0-0.5km	0.118*** (0.0152)	0.148*** (0.0123)	0.0860*** (0.0152)
Nearest PA within 0.5-1km	0.0963*** (0.0147)	0.0920*** (0.0119)	0.0562*** (0.0145)
Nearest PA within 1-2km	0.0569*** (0.0141)	0.0912*** (0.0113)	0.0323** (0.0138)
Nearest PA within 2-3km	0.0611*** (0.0136)	0.0811*** (0.0107)	0.0232* (0.0132)
Nearest PA within 3-4km	0.0571*** (0.0129)	0.0666*** (0.0101)	0.0150 (0.0123)
Nearest PA within 4-5km	0.0327*** (0.0118)	0.0542*** (0.00929)	0.0178 (0.0112)
Nearest PA within 5-6km	0.0333*** (0.0110)	0.0379*** (0.00817)	-0.000604 (0.0101)
Nearest PA within 6-7km	0.0248** (0.0101)	0.0397*** (0.00670)	-0.000846 (0.00891)
Nearest PA within 7-8km	0.00957 (0.00758)	0.0118** (0.00529)	-0.00754 (0.00707)
% PA in 7km ring	-0.00405*** (0.00104)	0.000671 (0.000847)	-0.00381*** (0.00130)
% Non- PA in 7km ring	-0.00275*** (0.000486)	-0.000627 (0.000616)	-0.00559*** (0.000955)
Constant	13.49*** (0.210)	13.30*** (0.214)	13.24*** (0.228)
Controls (17)	Yes	Yes	Yes
Observations	67,862	78,452	57,030
R-squared	0.830	0.806	0.808
F statistic	349.5	281.8	179.9
Root MSE	0.175	0.183	0.190

Notes: See Table 4. Dependent variable is the natural log of transaction price. All models include fixed effects for year, quarter and ZIP4 area. Specifications (7), (8), and (9) include observations that are located within Functional Urban Areas (FUAs) that are metropolitan, urban, and non-urban, respectively. Clustered standard errors (ZIP6) are in parentheses.

***, **, * Indicate significance at 1%, 5% and 10%, respectively.

prices extend. Positive price-effects stretch across 7 kilometers for *metropolitan* regions, 8 kilometers for *urban* regions, and 3 kilometers for *non-urban* regions. In interpreting these results, we can notice the relatively short distance across which price-effects appear in model (9) for properties in non-urban regions. Urban amenities are typically low in non-urban regions, so the availability of natural space amenities may be at the forefront of buyers' residential location decisions (Deller et al. 2001). Hence, if buyers consider properties in non-urban regions because they offer relatively more natural space amenities than urban or metropolitan regions, then the properties situated relatively farther away from attractive natural space are more likely to be evaluated as unsuitable. Conversely, buyers in metropolitan or urban regions may be willing to pay higher prices for properties proximate to PA natural space, even when that proximity is 7 or 8 kilometers, because the benefits of nearby attractive natural space amenities may compensate them for living in a high-density built environment (Sijtsma et al. 2012c).

VII. CONCLUDING DISCUSSION

The analysis carried out in this paper has operationalized a proxy for natural spaces perceived as *attractive* in general by residents in order to contribute to the growing literature on natural space effects on nearby residential property prices. The authors have elaborated on the notion that measures used in hedonic analysis should capture as precisely as possible the way potential property buyers 'perceive' an observed environmental good (Palmquist 2005). By doing so, it will be possible to appropriately reveal an environmental good's value-added to property prices. To be more succinct, our measures of perceived attractive natural space are based on combining land use data with data on the attractiveness of Dutch natural spaces as perceived by residents of the Netherlands. To date, such specific data on how natural spaces are perceived have not been applied in hedonic analyses. Our study connects the growing empirical literature on property prices with the empirical literature on subjective evaluations of natural spaces and landscapes.

The results discussed here provide supporting evidence that Dutch property buyers pay higher prices for properties located at a distance of up to 7 kilometers from attractive natural space. This evidence indicates that the economic benefits of living nearby natural space may extend over a wider distance than the maximum of 3.2 kilometers suggested in earlier studies if natural space is perceived as *attractive* (c.f. Mansfield et al. 2005). Specifically, the results for our main specification indicate that property buyers, on average, pay a 16.0% premium for properties within 0.5 kilometers of attractive natural space; and that this price premium decreases with distance smoothly, to 1.6% for properties 6 to 7 kilometers away (Figure 4). The price premium shows some variation depending on specification, but it is robust overall. Across specifications, attractive natural spaces are not found to add value to the selling price of properties beyond 7 kilometers. In addition to the robust main results, an additional empirical test suggests that the effect of attractive natural space on property prices varies in accordance with regional level of urbanization: the effect is found to vary between metropolitan, urban, and non-urban regions in both magnitude and in the distance across which it stretches.

From an empirical perspective it is noteworthy that when attractiveness is not taken into account, as in most hedonic studies on natural space, the distance over which natural spaces are capitalized in property prices is misunderstood. Our data and results imply that land use data by itself is not specific enough to construct measures which reflect how property buyers perceive the attractiveness of natural space. Measures of proximity to natural space, based on land use data only, are thus unlikely (on average) to capture the distance to nearby natural space that could effectively add considerable value to a property's price. It is not surprising that the few studies that do test explicitly for the distance over which natural space influences property prices, find effects from 2 to 3.2 kilometers at most, due to their having applied only land use data (e.g., Mansfield et al. 2005; Melichar and Kaprová 2013). Therefore, for the sake of accuracy, and prior to the measurement of proximity of properties to natural space, it seems prudent to ensure that the natural space data underlying a hedonic analysis reflects the way natural spaces are perceived. Our analysis here indicates that, although attractive natural spaces cover 6.83% of the total area of Dutch natural space, these *perceived attractive* natural spaces nevertheless represent the considerable economic benefits gained by living nearby natural space. Given these results, we hope that future hedonic studies pick up on perception-based natural space measurement.

The empirical implications discussed in the present paper are relevant to property price studies on natural space, as they provide quantitative information for land use-related decision making in public policy worldwide. In the highly urbanized Netherlands, such quantitative information is much sought after by central government (Dutch Ministry of Economic Affairs 2013), which has recently acknowledged that it aims explicitly to improve the supply of *attractive* natural spaces in close proximity to urban areas (Netherlands Environmental Assessment Agency 2014).

Our findings raise a major implication for public policy with regard to natural space near residential areas. The results discussed here clearly indicate that the relative size of attractive natural space effects on property prices decreases with distance; but they also imply that, different from previous studies, value may be added to more properties over greater distances, as illustrated in Figure 6. The aggregate economic benefits of living nearby attractive natural spaces may therefore be based to a limited degree on the value-added to the most nearby properties. The implication of this finding is that it seems to legitimize substantially larger investments in order

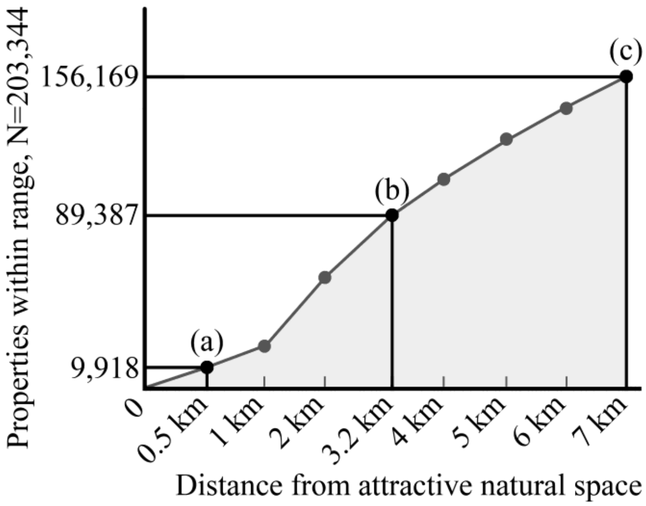

Figure 6. This figure gives the cumulative number of properties in our transaction data that surround attractive natural spaces at different distance ranges. The highlighted ranges reflect distances across which natural spaces impact on nearby property prices in accordance with findings by (a) conventional hedonic studies reviewed by Waltert and Schläpfer (2010); (b) Mansfield et al. (2005), who find effects over a longer distance (3.2 kilometer) than other hedonic studies, with the exception of the current study; and (c) the current study of attractive natural spaces.

to sustain the current supply of *attractive* natural spaces nearby cities than can be substantiated with existing hedonic studies. That is because when many people live within 7 kilometers from attractive natural space, it provides an aggregate welfare that is higher than would be assumed if only the welfare provided to the population within 2 or 3.2 kilometers is taken into account, as existing studies suggest. Indeed, perceived *attractive* natural space is shown in our study to offer considerable benefits to those who live 1, or 3, or up to 7 kilometers away.

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APPENDIX

When determining the appropriate search radius to use when clustering markers, there is no theoretical guidance on how to delineate natural spaces perceived as *attractive*. Therefore, this study evaluates multiple sets of attractive natural spaces constructed using different search radii (500m; 750m; 1,000m; 1,250m; and 1,500m). Statistical properties of these sets are described in Table A1. Each set is evaluated in a separate empirical model of property prices to ascertain which set performs best (see Table A2). The set constructed with a 1,250m search radius generates the relative highest effects on property prices significantly different from zero, thereby identifying 1,250 meters as the appropriate search radius. The set resulting from this search radius best captures how property buyers perceive attractive natural spaces in our study area.

Table A1. Statistical properties of each generated set of attractive (PA) natural spaces.

Search radius (m)	Clusters (#)	Markers within a cluster (#)	Total area clusters (km^2)
500	500	5,277	1,311
750	436	5,603	2,191
1,000	412	5,722	2,923
1,250	385	5,521	2,429
1,500	374	5,625	2,904

Table A2. Initial regression results for specifications that observe proximity measures for different sets of attractive (PA) natural spaces. Each set is constructed with a different search radius in clustering our value mapping survey data.

	A - 500 meter	B - 750 meter	C - 1,000 meter	D - 1,250 meter	E - 1,500 meter
Nearest PA within 0-0.5km	0.151*** (0.00503)	0.149*** (0.00454)	0.128*** (0.00431)	0.149*** (0.00450)	0.135*** (0.00431)
Nearest PA within 0.5-1km	0.102*** (0.00405)	0.0998*** (0.00386)	0.0873*** (0.00376)	0.101*** (0.00383)	0.0936*** (0.00380)
Nearest PA within 1-2km	0.0848*** (0.00298)	0.0847*** (0.00303)	0.0764*** (0.00299)	0.0842*** (0.00300)	0.0807*** (0.00305)
Nearest PA within 2-3km	0.0608*** (0.00286)	0.0607*** (0.00291)	0.0506*** (0.00288)	0.0610*** (0.00287)	0.0554*** (0.00294)
Nearest PA within 3-4km	0.0360*** (0.00286)	0.0337*** (0.00285)	0.0193*** (0.00288)	0.0366*** (0.00287)	0.0299*** (0.00287)
Nearest PA within 4-5km	0.0258*** (0.00276)	0.0319*** (0.00274)	0.0177*** (0.00274)	0.0347*** (0.00270)	0.0323*** (0.00275)
Nearest PA within 5-6km	0.0183*** (0.00270)	0.0291*** (0.00270)	0.0224*** (0.00272)	0.0293*** (0.00273)	0.0296*** (0.00276)
Nearest PA within 6-7km	0.0112*** (0.00272)	0.0156*** (0.00283)	0.00504* (0.00282)	0.0159*** (0.00280)	0.00460 (0.00286)
Nearest PA within 7-8km	-0.000821 (0.00273)	0.00127 (0.00278)	-0.000449 (0.00280)	0.00188 (0.00281)	0.00353 (0.00284)
% PA in 7km ring	0.00574*** (0.000278)	0.00293*** (0.000207)	0.00220*** (0.000187)	0.00222*** (0.000191)	0.00194*** (0.000179)
% Non-PA in 7km ring	-0.00208*** (0.000104)	-0.00206*** (0.000104)	-0.00213*** (0.000104)	-0.00205*** (0.000104)	-0.00208*** (0.000104)
Constant	11.43*** (0.0191)	11.43*** (0.0192)	11.45*** (0.0192)	11.43*** (0.0192)	11.44*** (0.0192)
Controls (17)	Yes	Yes	Yes	Yes	Yes
Observations	203,344	203,344	203,344	203,344	203,344
R-squared	0.749	0.749	0.749	0.749	0.748
F statistic	2956	2952	2958	2950	2951
Root MSE	0.213	0.214	0.214	0.214	0.214

Notes: Dependent variable is the natural log of transaction price. The specifications are equal except for their observations of different sets of PA natural spaces. Clustered standard errors (ZIP6) are in parentheses.
***, **, * indicate significance at 1%, 5%, and 10%, respectively.

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[1] This area size compares to approximately one-fourth of the 150,000 km² land mass of the state of Florida.

[2] The reader may notice that this implies emphasis on cultural ecosystem services rather than regulatory, provisioning, and supporting ecosystem services (MEA 2005).

[3] Even though, at the national scale any natural space in the study area could be marked, these markers may still be placed nearby dense residential areas. This is illustrated by the .25, .50, and .75 quantile values for kilometer distances between the national markers and (intermediate) urban areas, as defined in section IV, which are 2.96, 6.64, and 11.2, respectively.

[4] We used subsamples of the full HSM sample (N=8,613) to evaluate whether using incrementally (10% point) more markers leads to the observation of 'new' attractive natural spaces that would remain unobserved from a one-increment smaller subsample. The number of 'newly' identified attractive natural spaces falls quite sharply for subsamples larger than 60% of the full sample, and becomes relatively small for the full sample itself. This indicates the full sample's appropriateness for our analysis.

[5] We compared the distribution of home locations of HSM respondents in relation to the total Dutch population by the degree of local urbanization – using Statistics Netherlands 500x500m grid-data on the general population in 2011, and the definitions of local urbanization discussed in section IV. The shares of respondents (the shares of total Dutch population are in captions) in non-urban, intermediate urban, and urban locations are 10.65% (19.07%), 36.37% (37.11%), and 52.98% (43.82%), respectively. It is noteworthy that the share of respondents is 8.4% points off in non-urban locations, which in the Netherlands is strongly tied in with urban areas (Delfmann

et al. 2014); but overall, the distribution of HSM respondents is similar to that of the (mostly urban) Dutch population. Nevertheless, we examined whether regional under- or overrepresentation is present in the spatial distribution of HSM markers, given that the spatial distribution of HSM respondents varies across our study area (as does the general population). We compared the distribution of the markers observed in the full sample across the Eurostat NUTS-2 regions (in the Netherlands) plus the subsample of markers from opt-in respondents, with the distribution of a subsample of markers from respondents to a 'regionally balanced' stratified HSM survey: 100 respondents per each of the 12 Dutch provinces. With the exception of a slight overrepresentation of the full sample's markers in the Amsterdam area located within the NUTS-2 region of North-Holland, the (sub)samples' spatial distributions of HSM markers are similar. Hence, when we identify attractive natural spaces within our land use data using the procedure described in section II, we are able to use the full sample of national HSM markers (Figure 2c).

[6] For comparison, when all natural spaces in our land use data are considered, properties' mean distance to the nearest natural space is 0.14 kilometer. The mean distance to PA natural space (4.63 kilometer), being higher, follows from PA natural space covering 6.83% of the total area of natural spaces in our land use data.

[7] From the full transaction dataset (N=293,621) we use only observations of secondary market transactions of single family properties with a permanent residential function. These two filters remove 6,624 observations. We remove observations in the upper and lower 0.5 percentiles of the distribution of price and living area to control for non-arm's length transactions and outliers, respectively. This eliminates 3,674 observations, in addition to the removal of 6,402 observations

with no data on living area. We disregard 11,713 observations of properties built before 1905, and remove all investment objects, partially rented out properties, and properties associated with land lease contracts. These further filters remove 20,843 observations. 1,344 observations describe transactions of mobile homes, houseboats, recreational homes, estates, or service flats, and are removed accordingly. Furthermore, we remove 17,027 and 338 observations that have incomplete data on property address and locational controls, respectively. Lastly, because our main model specification includes the share of land cover of Dutch natural space within 7 kilometers of transacted properties, we cull all 22,312 observations of properties located within 7 kilometers of countries bordering the Netherlands, i.e., Belgium and Germany. Data on national borders have been acquired from Eurostat.

[8] Based on a notion of equilibrium, the hedonic price model uses information from market prices of a heterogeneous good, like property, to monetize a change in utility of a marginal change in an attribute of the observed good (Rosen 1974). In the case of property, attributes include structural characteristics, locational aspects, and characteristics of the surrounding environment. A detailed discussion of the theory and assumptions underpinning the property hedonic price model can be found in Palmquist (2005).

[9] The interpretation of the coefficients for continuous variables is straightforward, as these give approximately the percentage change in property price associated with a unit change in the independent variable.

[10] Fixed effects, which account for spatial clustering of property prices, do not control for property-specific characteristics that are possibly correlated with proximity to PA natural space. If such correlations are present, these could be accounted for by estimating a Repeat Sales (RS)

model. Estimation of an RS model requires the observation of changes in PA natural space over time; such information is, however, not included in our cross-sectional data. A cross-sectional alternative to the RS model is the Pseudo Repeat Sales (ps-RS) model outlined in Guo et al. (2014). The ps-RS model uses information on the first differences of the prices and characteristics of pairs of properties that are located close to each other – which may have similar (structural) characteristics. So, any observed or unobserved characteristics that paired properties share are cancelled out in the ps-RS model. In our ps-RS specification, properties were paired for having sold consecutively in time and, importantly, their being located within the same zip code area (ZIP4; N=3,255). We used areas at the ZIP4 scale, as this is the lowest spatial scale at which we were able to observe within-pair variation in discrete distances to the nearest PA natural space. The results for PA natural space measures in the ZIP4-level ps-RS model, available from the authors, were found to be very similar to those in the ZIP4-fixed-effects model (3). This gives some assurance that, in our data, accounting for spatial clustering of property prices is sufficient for identification of PA natural space's capitalization in property prices.

[11] Building locations and surfaces are derived from the Registers for Addresses and Buildings (BAG), maintained by the Netherlands Cadastre, Land Registry and Mapping Agency, which includes all buildings in the Netherlands. Of the transacted properties that we observe, 1.63% are indicated as providing a view on PA natural space, respectively. We checked if PA and non-PA natural spaces are similarly 'viewable' across our study area. We consider that the ratio between the numbers of transacted properties with a view on non-PA and PA natural space is 15.4, similar to the 13.6 ratio of all non-PA and PA natural space total areas. Therefore, PA and non-PA natural spaces are about as 'viewable' as they are 'present' within our study area.

[12] In an alternative view-specification, we have also included a control variable for view on non-PA natural space. Resulting estimates indicated that model (6) coefficients for proximity and view variables that pertain to PA natural space, are very insensitive to this change in specification.

[13] In exploratory specifications we included separate measures of distance, at discrete intervals, for natural spaces of distinct land use types. This approach, similar for example, to Melichar and Kaprová (2013), ignored differences in perceived attractiveness. Resulting estimates of effects on property prices were spurious and not sufficient for the robustness checks used in this paper. Only coefficients for proximity to open dry nature were found to yield somewhat robust economic benefits to property buyers at estimates of this study's spatial scale.

[14] Detailed results for these models are available from the authors upon request.

[15] Findings by Gibbons, Mourato, and Resende (2014) implicitly confirm this when they estimate the effect of various natural spaces on English property prices whilst restricting their full sample to major metropolitan regions. In doing so, they find higher price effects compared to those found using their full sample; however, the distances across which these effects stretch is not evaluated.