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Do people value environmental goods? Evidence from the Netherlands

Koen van Ruijven[a,b]* and Joep Tijm[a]

a CPB Netherlands Bureau for Economic Policy Analysis, P.O. Box 80510, 2508 GM, The Hague, The Netherlands

b Department of Spatial Economics, Faculty of Economics and Business Administration, Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands

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Abstract

This paper studies the relationship between environmental goods and housing prices. We use hedonic pricing in the entirety of the Netherlands to estimate correlations between the air quality, less noise pollution, green scenery, and water scenery, simultaneously. We show the importance of including related sets of environmental goods. We find that households particularly value noise pollution and green and water amenities within close distance of their house. The housing price effects of air quality and green over distances larger than 200 meters is small. These results suggests that households mainly value those environmental goods that are directly experienced. A comparison of our hedonic price results to the literature studying the monetary health effects indicates that people only partially internalize the health effects of environmental goods.

JEL classification: Q51, Q53

Keywords: Hedonic pricing, environmental goods, functional form

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1. Introduction

Since its inception by Rosen (1974), the hedonic price method has been used in a wide array of circumstances to infer the value of nonmarket goods, such as crime exposure (Pope, 2008), exposure to hazardous waste sites (Greenstone & Gallagher, 2008), and exposure to wind turbines (Droës & Koster, 2016). This study uses hedonic pricing as a method to infer the relationship of multiple environmental (dis)amenities with house prices in the Netherlands.

The compensating equilibrium asserts the hypothesis that environmental factors are likely to be reflected in the residential property market. To illustrate this, we expect households are only willing to accept negative health risks of higher air and noise pollution if and only if they are compensated by lower residential property prices (Davis, 2004).[1] Therefore, on the margin of purchasing a dwelling, households determine the extent of the compensating equilibrium; the price they are willing to accept for higher health risk. We expect a similar price mechanism to hold for green and water scenery. Households are likely to only accept to move to a location with lower green or water scenery if they are compensated with lower residential property prices.

Being faced with the econometric challenge of the interrelatedness of environmental variables (Ridker and Henning, 1967), we simultaneously estimate the compensating equilibria for both environmental disamenties (air and noise pollution) and amenities (the percentage green and water) using hedonic pricing methodology. The simultaneous estimation is necessary because of the overlap in the emittance of noise and air pollution. Earlier literature has traditionality only considered one environmental disamenity at a time (Kim et al., 2003; Cohen and Coughlin, 2008; Anselin and Lozano-Garcia, 2008; Andersson et al. 2010). On top of that, the presence of trees and open space tends to mitigate levels of air and noise pollution. Omitting either of these environmental variables may therefore lead to an overestimation of the effect of environmental (dis)amenities (Thayer et al., 1992).

To investigate the extent of the compensating equilibria, we use a rich dataset of over 80 percent of all Dutch housing transactions during 2016. We combine this with detailed data provided by the Dutch Institute for Public Health and the Environment (RIVM) on the exposure of citizen to different environmental goods. Our selection of variables for the set of environmental disamenities is motivated by the health consequences. We employ particular matter ($PM_{2.5}$)[2] as indicator for air pollution, as it is described as being air pollutions' leading cause of mortality (WHO, 2021). For noise pollution we use temporally weighted decibels (Lden), since noise emitted in the evening at and night produces stronger health effects. The selection of variables for the set of environmental amenities is primarily motivated by the level of detail that is provided to us by these data. For the presence of green and water, we computed the percentage around houses within distance bands up to 1500m. Since we expect a different willingness to pay for different types of greenery, we distinguish two types: *(i)* trees, and *(ii)* the combination of grass and shrubs. The use of distance bands in combination with percentages enables us to determine both a) the distance to which people are willing to pay for green and water around their home and b) whether people have a different appreciation for higher versus lower percentages of green and water scenery around their house. Even though we are not explicitly able to distinguish

[1] Next to health effects, we note that the exposure of air and noise pollution is associated with lower productivity levels (e.g. Graff Zivin & Neidell, 2012). Since lower productivity levels are translated into lower wages, the compensating equilibrium may not only reflect the discounted future health costs of individuals, but also the discounted costs of lower productivity levels.

[2] As alternative measures, we separately estimate the effects of PM_{10} and nitrogen dioxide (NO_2).

between different categories of green (parks, nature) and water (canals, rivers, lakes), the level of detail does enable us to distinguish between the difference in relationships of sparse levels relative to dense levels of green and water, even within neighbourhoods.

The Netherlands provide an interesting context for the simultaneous estimation of environmental goods because of its considerable variation among regions. For example, in 2016 about 4 out of 10 of the Dutch households experience pollution levels deemed harmful by the World Health Organization.[3] Second, since the Netherlands is one of the most densely populated countries in the world and over 60 percent of the Dutch land use is dedicated to farmland, the exposure of the Dutch to natural reserves is limited and subject to considerable variation across space. Third, a significant part of the Netherlands is located below sea level, which leads to a large variation in the exposure of the Dutch in proximity to water. This enables us to be the first to estimate the housing price effects of varying amounts of water in direct proximity around houses.

With the identification challenges of hedonic methods in mind (Kuminoff et al., 2014), we take a number of steps to absorb confounding omitted variables in the estimation environmental variables on housing prices. First, since time-invariant effects may be correlated with environmental variables, we include spatial fixed effects in our model of cross sectional data. Our use of spatial effects prohibits us from being able to capture the housing price effects of green and water amenities at large distances from the postal code area (like woodlands, sea and other nature). That is, since the within-variation for these amenities is scarce, these effects are captured by the postal code fixed effects. Second, since the availability (and abundance) of consumer and producer amenities may be correlated with environmental amenities (Li and Brown, 1980), we include a set of observed consumer and producer amenities that may simultaneously affect housing prices. To this end, we use a rich set of data on consumer and producer amenities on the neighbourhood level. Third, we address concerns about misspecification and heterogeneity in preferences (Cropper et al., 1988) by allowing for potential nonlinearities in the hedonic price schedule for environmental (dis)amenities. Fourth, we assess the potential impact of unobserved confounders using the methodology developed by Oster (2019).

Even though we devote attention to absorb confounding omitted variables, our results cannot be interpreted as causal since we do not exploit quasi-experimental variation in the environmental variables. The results in this paper must therefore be interpreted as (conditional) correlations. We do not need to estimate strictly causal effects however to show that environmental variables are related and that omitting noise as a control when estimating the effect of air pollution leads to an overestimation.

Our results suggest that households particularly value environmental amenities within close proximity of their house. We show that there is a positive association between housing prices and the percentage green scenery up to 200 meters and water up to 1000 meters around a house. The results for green scenery exhibit a pattern of diminishing returns over the distance. This implies the largest relations are found within 50 meters of a house, and the housing price effects decreases up to a distance of 200 meters after which the results become statistically insignificant. We do not find a similar diminishing returns pattern for water.

[3] These people live at locations at which either the recommend standards by the World Health Organization (WHO) of noise pollution (54 dB road noise), or air pollution ($PM_{2.5}$ over 5 mg/m3) are exceeded. The recommended standards by the World Health Organization can be found here (link).

Interestingly, since we allow for nonlinearities in the hedonic price schedule, we show that within the distances of 200 meters for green scenery and 1000 meters for water scenery, the coefficient increases with the percentage green and water. As an illustrating example, we find that a 10%-point increase in the percentage grass and shrubs (trees) within 50 meters is associated with a rising increase in residential property prices from 1% up to 4% (1% to 3%). These results may be driven by the fact that people have a different appreciation for different types of green and water. For example, a city park is valued more than a single tree in the area.

Our results on environmental disamenities suggests households particularly value noise pollution. The hedonic price schedule of noise pollution has a cubic functional form, reflecting that households primarily seem to value less noise at the tails of the distribution (within the range of 20 to 40 dB and 60 to 80 dB). At these tails, each one dB increase is correlated with a decrease in residential property prices by 0.8 to 1.5%. Lastly, the hedonic price schedule for air pollution exhibits a linear functional form. Our results suggest that each μg/m^3 increase in $PM_{2.5}$ is correlated with a decrease in residential property prices by 0.46%.

Our results have important implications for policy, since they suggest that households may have a mild valuation for environmental goods they do not directly experience. This is particularly relevant for air pollution. Recent studies (e.g. Deryugina et al., 2019) indicate that the health costs are significantly higher than our estimates of the economic value that household place on air pollution, suggesting that households only partially internalize the social costs of air pollution. This suggests that the economic value of air pollution in terms hedonic prices may not necessarily be a good indicator for policy.

With this paper we contribute to the to the strand of literature that values the willingness to pay for environmental variables, summarized by Smith & Huang (1995) on air pollution, Kopsch (2016) on noise pollution, and Boyle and Kiel (2001); Mendelsohn and Olmstead (2009) on environmental amenities. Most previous studies only estimate the willingness to pay for a single environmental (dis)amenity, and are of a limited geographical scope. Our paper is the first to estimate correlations between the air quality, less noise pollution, green scenery, and water scenery, simultaneously. We show the importance of including related sets of environmental goods. Not accounting for these variables may lead to an overestimation of the valuation of households for environmental goods. This is particularly relevant in quasi-experimental settings like evaluations of area development projects affecting multiple environmental goods at the same time.

Furthermore, we show the importance of allowing for nonlinearities in the hedonic price schedule for environmental goods. It seems that large gains in accuracy can be attained by moving away from the standard log-linear specifications (Kuminoff et al., 2010).

This paper proceeds as follows. Section 2 presents the empirical strategy. Section 3 describes the data and lists the descriptive statistics. Section 4 presents the empirical results and includes a number of robustness checks. Section 5 closes with concluding remarks.

2. Empirical strategy

We are interested in the relationship between environmental (dis)amenities, denoted by $EV_{i,t}$, and residential property prices, denoted by $\log p_{i,n,r,t}$ where i refers to a property in neighborhood r and located in postal code n, and t is the month of transaction. The main specification is as follows[4]:

$$\log p_{i,n,r,t} = \alpha EV_i + \beta X_{i,t} + \gamma A_{i,r} + \delta D_{i,r} + \zeta S_{i,r} + \mu_n + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where the log-transformed price of a dwelling is explained by EV_i a vector comprising environmental (dis)amenities ($PM_{2.5}$, dB (Lden), green scenery, water scenery) and $X_{i,t}$ the set of residential property characteristics (included in Table 3).

Since environmental (dis)amenities are not randomly allocated across space (Small, 1975; Li and Brown, 1980), we include different sets of control variables that are likely to covary with the environmental variables while simultaneously affecting housing values (Sirmans et al., 2005). For this reason, the equation includes a set of producer and consumer amenities, denoted by $A_{i,r}$. These sets of variables are included due to the likelihood that producer amenities (e.g. the density of jobs) and consumer amenities (e.g. the density of restaurants and cultural heritage) are likely to covary with higher pollution levels, even though these variables have a positive (indirect) impact on housing values (Combes et al., 2008; Glaeser et al., 2001).[5]

Aside from environmental (dis)amenities not being randomly allocated across space, different types of households are also not randomly allocated across space (Tiebout, 1956). It is recognized that households sort themselves to locations dependent on their own characteristics in terms of income, education, and migration background, among others (Bayer et al., 2007). That is, the demographic and socio-economic characteristics of locations attract certain households, for instance when households treat affluent neighbors as an amenity, while other characteristics such as the percentage elderly people may not appeal to others. These differences in preferences may lead to (income) segregation across neighborhoods. If these preferences for demographic and socio-economic variables of neighborhoods covary with preferences for environmental goods, then our estimates of the willingness to pay may merely reflect the average willingness to pay of subpopulations (Chay and Greenstone, 2005). We account for the nonrandom sorting of households by including two vectors of control variables: one vector of demographic characteristics of households, denoted by $D_{i,r}$, and one vector of socio-economic characteristics of households, denoted by $S_{i,r}$. The complete list of each of the included variables on the neighborhood statistics ($A_{i,r}$, $D_{i,r}$, and $S_{i,r}$) is included in Appendix Table A2.

Furthermore, the equation includes postal code fixed effects, denoted by Z_n, to control for unobserved time-invariant differences between postal codes (Kuminoff et al., 2010) and time fixed effects (month dummies), denoted by T_t, to control for the trends in housing prices. The set of previously mentioned control variables $A_{i,r}$, $D_{i,r}$, $S_{i,r}$ are on the local neighborhood level and are located within postal codes. These variables therefore control for the within variation in

[4] A conceptual description of the hedonic price method in the context of environmental (dis)amenities is listed in Appendix section A2.

[5] Although we have a large set of potential control variables, we may not want to include them all in the regression equation due to risks of overfitting (Bateman et al., 2001). To infer whether our model includes too many controls, we perform a lasso methodology as a robustness check (see Appendix section A3 for econometric details). We also use the method developed by Oster (2019) to assess the importance of omitted variables in our regression model.

postal codes.[6] Lastly, $\varepsilon_{i,t}$ is the error term. The standard errors are clustered on spatial grids of 1km by 1km.[7] α, β, γ, δ, ζ are the parameters to be estimated. For a complete description of all vectors of control variables, we refer to Appendix Table A1.

Equation (2) examines the average willingness to pay of households for environmental (dis)amenities (α) under the assumption of linearity in the hedonic price schedules. However, as pointed out by Rosen (1974) there may be reasons to expect the hedonic price schedules could actually be nonlinear, reflecting heterogeneity in preferences and pointing to misspecification (Cropper et al., 1988). We provide two reasons. First, recent meta-analyses indicate that the health effects of environmental disamenities may be nonlinear (Chen & Hoek, 2020; WHO, 2021). For instance, it is recognized that the detrimental effects of noise pollution arise after certain cutoff thresholds are surpassed (above 50 dB). Second, the law of diminishing marginal utility is likely to apply. For example, households are likely to directly notice the difference between no green scenery around their house relative to presence of some green scenery. Whereas the difference between an already large amount of green scenery relative to an even larger amount of green scenery is harder to detect by households. For these reasons, we allow for potential nonlinearities in the willingness to pay for environmental goods by adding polynomials to the vector EV_i.

3. Data and descriptive statistics

This section describes the data that are employed to conduct the empirical analyses. We start by describing the data on environmental (dis)amenities, followed by a description of the data on residential property transactions and on neighborhood characteristics. For each of the data, we report descriptive statistics.

3.1. Environmental (dis)amenity data

Our empirical analysis relies on data on environmental (dis)amenities. For the disamenities of air and noise pollution, we use model data that are obtained from Dutch Institute for Public Health and the Environment (in Dutch Rijksinstituut voor Volksgezondheid en Milieu, RIVM). The data measure the air and noise pollution level for the entirety of the Netherlands during 2016. We use two measures for air pollution ($PM_{2.5}$ and NO_2) and one measure for noise pollution (decibels, in Lden[8]).

The construction of the data by the RIVM on air pollution consists of two stages (Sautar et al., 2020; Van Velze & Wesseling, 2015). In the first stage the RIVM collects data on all factors that emit pollutants. For instance, it collects the data on the number of pollutants emitted by individual businesses: the so-called point-sources (e.g. industry factories, farms, and waste incineration companies). This data is combined with line sources: data on the intensity of traffic on local roads and highways. The result of these combinations is a nationwide spatial map which indicates the total number of pollutants emitted on local grids. The data of the major polluters are used as input in the national dispersion model to determine the air pollution levels at spatial grids of 1 by 1

[6] On average there are about three neighborhoods located within each postal code.

[7] The national model that determines the air pollution levels in the Netherlands use the same 1 by 1km spatial grids. The national model is complemented by local inputs on a spatially detailed level (e.g. to compute the transmission of air pollution from highways, further details listed in the data section). As a robustness check, we therefore also use clustered errors on the lowest spatial grids possible (the lowest neighborhood level).

[8] The Lden measure (level day, evening, night) reflects the average noise transmitted over a day, although noise transmitted during the evening and night are 'penalized' with a 5db and 10db increment factor, respectively.

kilometers. The dispersion model takes a myriad of factors into account such the air pollution coming from neighboring countries, the wind speed, the wind direction, humidity, precipitation intensity and temperature.

Even though the national model produces air pollution levels on 1 by 1 kilometer grids, the local air pollution (on the housing level) can differ quite significantly. For this reason, a local model is used which stacks the input of the national model and uses local pollutants as input to determine the air pollution at a very local level of 10 by 10 meters. At this level the dispersion is influenced local factors such as the density of trees and the distance towards buildings. [9] In our analysis we use the data of the 10 by 10 meter grids.

The construction of the map for noise pollution follows a similar stacking procedure as in air pollution. Again the model employs a spatial map of all factors that emit (noise) pollution as input. The model then stacks the relative frequencies for each of these factors taking into account their occurrence. There are however a couple of differences with air pollution. The main difference is that the transmission of noise is subject to much smaller geographically defined locations (with traffic noise as main input). Consequently only a local model is used to determine the noise pollution. Moreover, the transmission of noise pollution is modelled in three dimensions, which takes into account the dimensions of the surroundings such as buildings.[10] The data are modelled on 10 by 10 meter grids, which we use in our analysis.

Figure 1 illustrates the air and noise pollution at the 10 by 10 meter grid level for the Netherlands during 2016. The upper side of the figure reports the particulate matter concentrations of fine particles of 2.5 μm or less ($PM_{2.5}$).[11] The bottom figure reports the decibel concentrations (Lden).[12] In the Appendix, we report a maps of the nitrogen dioxide (NO_2) concentration and of the particulate matter concentration of particles of 10 μm or less (PM_{10}).

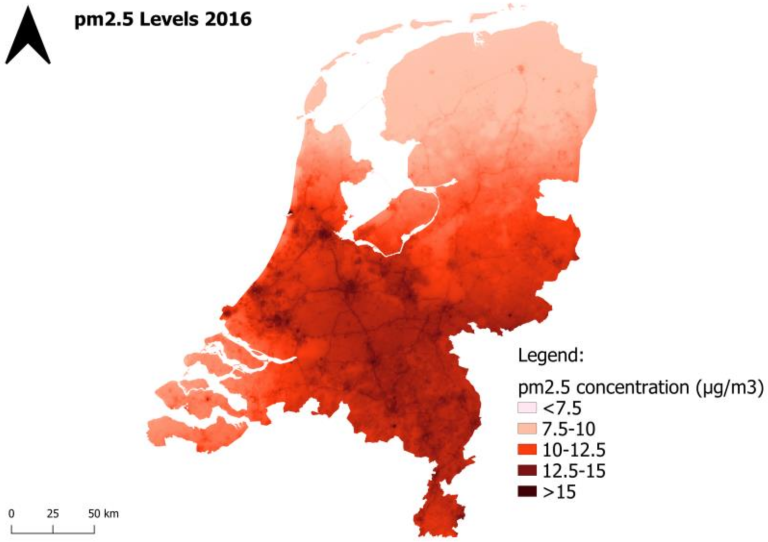
Figure 1 demonstrates that the air and noise pollution concentrations are higher than the recommend standards by the WHO (2021) in a significant part of the Netherlands. The WHO recommends to keep the human exposure of noise pollution below 54 decibels (Lden) for road noise. For air pollution ($PM_{2.5}$), the recommended standard are below 5 μm per cubic meter. Both panels clearly show the difference between the transmission in air pollution versus noise pollution. The transmission of the latter is much more local and concentrated around highways, airports and industries, whereas the transmission of the former covers much larger parts of the Netherlands. The transmission of the air pollution is heavily influenced by a few heavy polluting areas (industrial and portal activities along the coast, and mega farms around the provinces of Utrecht and Noord-Brabant).

[9] A detailed description of the air pollution model is listed in Sauter et al. (2020).

[10] Further details of the noise pollution model is listed in Schreurs et al. (2010).

[11] Particles at this level can, when being inhaled, be transmitted from the lungs to blood streams and the brain. This is associated increased health risk, such as respiratory complaints, cardiovascular disease and lung cancer (see (Anderson et al., 2012; Raaschou-Nielsen et al., 2013). As a consequence, the exposure to $PM_{2.5}$ is associated with an increased risk of earlier mortality (Chen et al., 2013).

[12] The exposure of people to noise pollution can cause increases in stress and hormone levels. In this way, noise pollution can lead to increases in blood pressure and heart rate, which disrupts the sleep structure. Moreover, noise pollution is associated with an increased incidence of arterial hypertension, myocardial infarction and stroke. (Münzel et al., 2014).



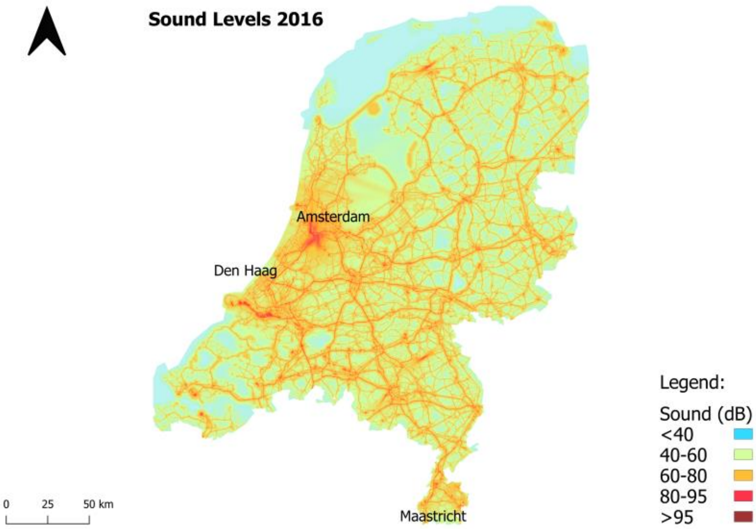


Figure 1: *The air pollution and noise pollution map of the Netherlands during 2016*

Notes: The upper figure shows the air pollution concentrations in terms of $PM_{2.5}$. Similar maps of the air pollution concentrations in terms of PM_{10} and NO_2 are outlined in the Data Appendix. The bottom figure shows the decibels in terms of Lden (level day, evening, night).

Our data on environmental amenities consists of two measures of green scenery and one measure of water scenery. For green scenery, we use raster data that are obtained from the RIVM and show the presence of vegetation (non-cropland) in the Netherlands during 2016. These data are constructed using infrared aerial photos. National height maps were used to divide vegetation into different measures: trees and other types (grass and shrubs)[13].

We adopt a similar categorization strategy for our measure of water scenery. The raster data, obtained from the Dutch Cadastre, Land Registry and national mapping agency (in Dutch; Kadaster), shows the exact location of all surface water in the Netherlands during 2016. This

[13] Since the measure of trees is based on aerial photos, the method cannot determine the land use below the trees (e.g. the presence of grass and shrubs). For this reason, our coefficients that exhibit the willingness to pay for trees may also partly comprise the willingness to pay for green scenery below the trees.

includes canals, rivers, ponds, lakes and the North sea.[14] Note that we do not divide our measure of water scenery into different scenery types. This is because our proportionality measure (percentage land coverage within a certain distance from a housing object) takes into account the presence of large amounts of water (e.g. lakes), relative to minor amounts (e.g. rivers and canals). We refer to Figure A2 in the Data Appendix for spatial maps of the Netherlands for green and water scenery.

Table 2 reports the descriptive statistics of the data on environmental (dis)amenities. The data correspond to the weighted average of our dataset on housing transactions in the Netherlands during 2016. The patterns exhibited by Figure 1 and the Appendix Figures A1 and A2 are shown in the table: there is clear heterogeneity across space in terms of the Dutch exposure to environmental (dis)amenties.

3.2. Residential property transaction data

Using geographic information system software (QGIS), we link the maps containing environmental (dis)amenties to a dataset that contains detailed information about residential property transactions in 2016. The residential property data are drawn from administrative records of the Dutch Association of Real Estate Brokers and Experts (in Dutch NVM). Over 80 percent of all housing transactions in the Netherlands are handled by real estate agents attached to this organization. The dataset contains a number of 146,823 housing transactions for 2016.[15] Each observation comprises a rich set of information on the location (e.g. its address), the transaction (e.g. the transaction price and the date of sale), and the structural characteristics of the housing object (e.g. the type of housing, the floor space, and the maintenance quality). The descriptive statistics are reported in Table 3.

3.3. Neighborhood characteristics

Since we are concerned that environmental (dis)amenities are not randomly allocated across space, we use different sets of neighborhood characteristics as control variables. The data on neighborhood characteristics are obtained from Statistics Netherlands (in Dutch, Centraal Bureau voor de Statistiek). We use neighborhood characteristics on the level of producer amenities (e.g. number of businesses, subdivided by sector types), and the level of consumer amenities (e.g. the number of restaurants and schools). Each of these neighborhood characteristics are likely to covary with the environmental variables while simultaneously affecting housing values. We make sure that each of these variables do not merely reflect the size of the neighborhood by constructing relative variables, either comprising its number within certain distances (e.g. the number of restaurants within 1km), or by using percentages (e.g. percentage inhabitants elderly benefits). For a complete list of the descriptive statistics of our data on neighborhood characteristics and spatial (dis)amenities, we refer to Appendix Table A2.

[14]. The exposure of people to water is associated with positive health effects, albeit to a lesser and more indirect extent (Pasanen et al., 2019; White et al., 2020).The Netherlands is also known as the "Lowlands", because over 25% of the Netherlands is located below sea level To illustrate this: our data shows that over 3/4th of all housing transactions have water within a distance of 200 meters.

[15] The steps conducted to clean the dataset on residential property transactions is listed in the Data appendix Table A1.

Table 2: Environmental Variable Statistics

	Mean	Standard deviation	Description
Pollution variables			
$PM_{2.5}$	10.86	1.50	Concentration particulate matter of particles <2.5 μm/m^3
PM_{10}	18.05	1.79	Concentration particulate matter of particles <10 μm/m^3
NO_2	19.85	4.76	Concentration nitrogen dioxide, in μm/m^3
dB	54.09	5.55	Noise pollution level, in decibels (Lden)
Green scenery			
Grass and shrubs within 50m	20.22	11.06	Percentage grass & shrubs within 50 meters house
Grass and shrubs (50-100m)	18.23	11.38	Percentage grass & shrubs between 50 and 100 meters house
Grass and shrubs (100-200m)	22.73	9.64	Percentage grass & shrubs between 100 and 200 meters house
Grass and shrubs (200-500m)	24.74	10.01	Percentage grass & shrubs between 200 and 500 meters house
Grass and shrubs (500-1000m)	19.33	10.77	Percentage grass & shrubs between 500 and 1000 meters house
Trees within 50m	16.77	10.36	Percentage trees within 50 meters house
Trees between 50-100m	20.34	10.21	Percentage trees between 50 and 100 meters house
Trees between 100-200m	21.02	8.79	Percentage trees between 100 and 200 meters house
Trees between 200-500m	24.98	8.58	Percentage trees between 200 and 500 meters house
Trees between 500-1000m	28.25	8.86	Percentage trees between 500 and 1000 meters house
Water scenery			
Water within 50m	7.03	13.53	Percentage water within 50 meters house
Water between 50-100m	9.85	13.19	Percentage water between 50 and 100 meters house
Water between 100-200m	11.01	11.11	Percentage water between 100 and 200 meters house
Water between 200-500m	14.10	10.64	Percentage water between 200 and 500 meters house
Water between 500-1000m	16.84	10.57	Percentage water between 500 and 1000 meters house

Notes: The number of observations is 146,823.

Table 3: *Residence-Specific Descriptive Statistics*

	Mean	Standard deviation	Description
Transaction price	245,228	124,591	Transaction price of the residence, current prices (2016)
Structural characteristics			
Floor space (m^2)	119.54	42.46	The number of square meters floor space of the residence
Living space (m^3)	380.38	154.41	The number of cubic meters living space of the residence
Parcel size (m^2)	307.45	668.21	The number of square meters parcel size of the residence
Number of rooms	4.59	1.45	The number of rooms in the residence
Number of floors	2.35	0.86	The number of floors in the residence
Residence type			
i) Apartment			Dummy variable that equals one if the residence is an apartment and…
Downstairs	0.03	0.18	located downstairs of a building
Upstairs	0.05	0.22	located upstairs of a building
Porch	0.10	0.30	located in a porch flat
Gallery	0.06	0.23	located in a gallery flat
Other	0.02	0.15	either located in a maisonette, or comprising both the upper and lower floor
ii) House			Dummy variable that equals one if the residence is a house and…
Intermediate	0.31	0.46	located in between other houses
Corner	0.12	0.33	located at a corner
Semi-detached	0.16	0.37	semi- detached from other houses
Detached	0.14	0.35	completely detached from other houses
Dwelling quality			
Maintenance quality inside (1-9)	5.89	1.41	Quality of maintenance inside the dwelling, ranging from bad, bad (1) to excellent (9)
Maintenance quality outside (1-9)	5.93	1.30	Quality of maintenance at the exterior of the dwelling, ranging from bad (1) to excellent (9)
Maintenance of garden (1-5)	3.53	0.86	Quality of maintenance of the garden, ranging from no garden existent (1) to very-well-kept (5)
Insulation quality (0-5)	2.38	1.78	Dwelling has no isolation (0), one-layered isolation, two-layered, three-layered, four-layered, or 5-layered (or full) isolation
Days for sale	216.15	318.99	Difference in number of days between first on the market and transaction

Notes: The number of observations is 146,823. The non-reported variables included in the $X_{i,t}$ vector of equation (2) include: whether the dwelling has a parking space, whether the dwelling is a listed building, whether the dwelling has an attic, the number of balconies, roof terraces, toilet rooms, bathrooms of the dwelling, the building period of the dwelling (in unequally distributed time-periods) and the type of heating system within the dwelling.

4. Results

In this section, we provide the results of the willingness to pay for environmental (dis)amenities. We start by providing a number of lessons of estimation equation (1). In section 4.2 we present our main results when we allow for nonlinearities in the willingness to pay. Section 4.3 determines the robustness of the main results by a number of sensitivity checks.

4.1. Lessons of linear estimates

Table 4 reports within estimation regression results of equation (2). All regressions reported in columns (1) to (5) include month fixed effects, neighborhood fixed effects and a set of residential property characteristics. Columns (4) and (5) stepwise include sets of control variables. In all specifications, the standard errors are clustered at 1 by 1km grids. Each of the reported coefficients can be interpreted as the marginal association of a one-point increase in an environmental (dis)amenity (i.e. $\mu g/m^3$ for air pollution, dB for noise pollution, and % for environmental (dis)amenities) on residential property prices.

Table 4 teaches a number of lessons. First, we learn that the sets of environmental amenities (tree coverage and water) and environmental disamenities ($PM_{2.5}$ and NO_2) are often found together. In case one does not account for these interrelated sets of (dis)amenities, one may mistakenly overestimate the willingness to pay due to omitted variables. The importance of including interrelated sets of environmental (dis)amenities is shown by columns (1) and (2), which omit different sets of variables in the regression analysis. In column (1) the variables NO_2, dB and a set of variables of tree scenery are omitted, while column (2) only omits the variables NO_2 and dB. Column (2) shows that when the variables of tree scenery are included the coefficients of $PM_{2.5}$ and water scenery are adjusted downwards significantly. This suggests that *(i)* trees tend to be located close to water, and *(ii)* that air pollution is lower in locations with more tree coverage. Moreover, column (3) shows a similar downward adjustment in the coefficient of $PM_{2.5}$ when the noise pollution is included, indicating these are positively correlated.

Second, we learn that even though environmental (dis)amenities are not randomly allocated across space, the inclusion of a large set of producer amenities, consumer amenities, and disamenities has a modest impact on the coefficients. This is shown by column (4). The reason for the modest impact is because the within estimator takes account of the time-invariant between variation of neighborhoods. It suggests that the one year within-variation in local neighborhoods for these (dis)amenities is limited.

Third, column (5) and (6) reveal that the inclusion of demographic and socio-economic variables lead to a downward adjustment of the coefficients. These results seem to confirm the notion that patterns of sorting are related to the willingness to pay for environmental goods. Taken from the different sets of environmental variables, we find that the adjustment is largest for $PM_{2.5}$, which declines sharply in terms of significance and coefficient size. This suggests that relatively affluent households sort themselves into high socio-economic status neighborhoods with low levels of air pollution ($PM_{2.5}$).

Table 4: *What is the Willingness to Pay for Environmental Variables?*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pollution							
$PM_{2.5}$	-0.0145***	-0.00976***	-0.00739***	-0.00624***	-0.00587**	0.00382	0.0130
	(0.00263)	(0.00261)	(0.00259)	(0.00239)	(0.00231)		
dB			-0.00189***	-0.00189***	-0.00179***	-0.00176	-0.00166
			(0.000153)	(0.000146)	(0.000145)		
Green scenery							
% Grass & shrubs within 50 meters house	0.00227***	0.00229***	0.00226***	0.00222***	0.00222***	0.00197	0.00154
	(0.0000948)	(0.0000968)	(0.0000965)	(0.0000915)	(0.0000908)		
% Grass & shrubs between 50 and 100 meters house	0.000766***	0.000743***	0.000688***	0.000613***	0.000577***	-0.000104	-0.000767
	(0.000102)	(0.000106)	(0.000105)	(0.0000980)	(0.0000975)		
% Grass & shrubs between 100 and 200 meters house	0.000510***	0.000523***	0.000587***	0.000375***	0.000374***	0.000593	0.000275
	(0.000118)	(0.000122)	(0.000122)	(0.000115)	(0.000115)		
% Grass & shrubs between 200 and 500 meters house	-0.00126***	-0.00108***	-0.00111***	-0.000866***	-0.000805***	-0.00138	-0.00201
	(0.000146)	(0.000151)	(0.000151)	(0.000148)	(0.000147)		
% Grass & shrubs between 500 and 1000 meters house	-0.00172***	-0.00134***	-0.00149***	-0.000347	-0.000268	-0.000122	0.000146
	(0.000215)	(0.000233)	(0.000233)	(0.000232)	(0.000228)		
% Grass & shrubs between 1000 and 1500 meters house	-0.00144***	-0.000958*	-0.000937*	0.000408	0.000583	0.000312	-0.000814
	(0.000500)	(0.000532)	(0.000529)	(0.000507)	(0.000497)		
% Trees within 50 meters house		0.00123***	0.00127***	0.00130***	0.00128***	0.00119	0.00117
		(0.0000933)	(0.0000932)	(0.0000881)	(0.0000876)		
% Trees between 50 and 100 meters house		0.000356***	0.000383***	0.000345***	0.000348***	0.000310	-0.00114
		(0.000105)	(0.000106)	(0.000103)	(0.000103)		
% Trees between 100 and 200 meters house		0.00102***	0.00104***	0.000963***	0.000975***	0.000880	0.000682
		(0.000124)	(0.000124)	(0.000119)	(0.000118)		
% Trees between 200 and 500 meters house		0.000544***	0.000477***	0.000378**	0.000332*	-0.000118	-0.000304
		(0.000181)	(0.000181)	(0.000174)	(0.000172)		
% Trees between 500 and 1000 meters house		0.000360	0.000235	0.000377	0.000312	-0.000156	-0.000447
		(0.000285)	(0.000285)	(0.000269)	(0.000265)		

% Trees between 1000 and 1500 meters house		0.000542 (0.000531)	0.00538 (0.000527)	0.000520 (0.000474)	0.000513 (0.000463)	0.000577	0.000914
Water scenery							
Percentage water within 50 meters house	0.00112*** (0.0000653)	0.000967*** (0.0000675)	0.000981*** (0.0000672)	0.000960*** (0.0000646)	0.000963*** (0.0000647)	0.0000913	0.000517
Percentage water between 50 and 100 meters house	0.000377*** (0.0000778)	0.000285*** (0.0000809)	0.000306*** (0.0000808)	0.000301*** (0.0000775)	0.000289*** (0.0000771)	0.000265	0.000140
Percentage water between 100 and 200 meters house	0.000399*** (0.000105)	0.000246** (0.000110)	0.000235** (0.000110)	0.000239** (0.000102)	0.000227** (0.000101)	-0.000112	-0.000662
Percentage water between 200 and 500 meters house	0.000591*** (0.000168)	0.000643*** (0.000173)	0.000645*** (0.000172)	0.000670*** (0.000157)	0.000558*** (0.000155)	-0.000206	-0.00109
Percentage water between 500 and 1000 meters house	0.0000643 (0.000213)	0.000276 (0.000213)	0.000217 (0.000211)	0.000453** (0.000199)	0.000521*** (0.000194)	0.000744	0.000381
Percentage water between 1000 and 1500 meters house	0.000162 (0.00103)	0.000782 (0.00103)	0.000704 (0.00103)	0.000888 (0.000916)	0.000880 (0.000899)	0.000506	0.0000865
Residential property characteristics	Y	Y	Y	Y	Y	Y	Y
Fixed effects (neighborhood + month)	Y	Y	Y	Y	Y	Y	Y
Amenities				Y	Y	Y	Y
Demographic and socio-economic characteristics					Y	Y	Y
OVB R_{max}						$\approx 1.1\times \tilde{R}$	$\approx 1.2\times \tilde{R}$
R-squared	0.803	0.805	0.806	0.814	0.816	0.900	0.980

Notes: This table reports the statistical association between environmental variables and log-transformed residential property prices. For a description of the environmental variables. see Table 2. All regressions include over 4/5th of the residential property transactions in the Netherlands during the year 2016. The number of observations is 146,823. All regressions include month fixed effects. neighborhood fixed effects and a set of residential property characteristics. Columns (4) and (5) stepwise include vectors of control variables. Column (4) adds a set of producer amenities and consumer amenities. Column (5) includes a set of demographic and socio-economic characteristics of the local neighborhood. Column (6) and (7) provide the coefficients based on the assumption that unobserved variables to have a proportional impact as the observed variables on the coefficient (Oster, 2019), using a R^2max multiplication factor of approximately 1.1 and 1.2, respectively. For a description of the vectors of control variables. see Appendix Table A1. Standard errors clustered on 1 by 1km spatial grids are reported in parentheses Statistical significance denoted by * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Fourth, as we hypothesized, the coefficients for environmental amenities, are largest in close proximity to the housing object, and decline as the distance from the house increases. Beyond a distance of 1000 meters the coefficient for each of the environmental amenities becomes statistically insignificant. The distance decay varies by environmental amenity, The distance decay is strongest in the willingness to pay for grass and shrubs. Surprisingly the coefficients for grass and shrubs are slightly larger than the coefficients for trees within distances of 200 meter. This suggest people prefer a free green outlook from their house, even above tree scenery. In distances between 200 and 500 meters we find a negative relationship for grass and shrubs. Since we do not find a similar negative pattern for trees after 200 meters, this is likely explained by the negative effects of (intensive) farming not taken up by the pollution variables. The distance decay is the weakest and almost negligible in the housing price relationship for water scenery. Our results suggest that people are willing to pay for more water around their house, but the distance to the water is less important.

Even though we include a large number of control variables in Table 4, we still may be concerned about unobserved characteristics that are related to our set of environmental variables and simultaneously influence housing prices. For instance, some factors like quality of public space are left unobserved. A method to infer the importance of unobserved variables is provided by Oster (2019). This method provides an indication of the degree of omitted variable bias building upon the assumption that the effect of observed variables on the coefficients of interest are informative about the effect of unobserved variables. In particular, the degree to which the coefficients of interest and the R^2 change when including observed controls can be used to determine the impact of unobserved controls.

Two key decisions that have to be made when applying the method by Oster (2019) is *i)* the degree of selection of unobserved variables relative to selection on observed variables (δ) and *ii)* the how much of the unobserved variance left in the model we want to explain (R^2max). Oster argues that a reasonable upper bound for *i)* is to assume a proportional effect of unobserved variables relative to observed variables ($\delta = 1$), and for *ii)* using a R^2 that is 1.3 times larger, while at the same time not using the upper bound of R^2 at 1. The latter is too restrictive due to measurement and idiosyncratic error. We therefore employ a R^2max at 0.90 and 0.98 respectively, which approximately coincide with a factor of 1.1 and 1.2 relative to the R^2 of the full model with observed controls. The results are shown in columns (6) and (7) and displayed in Appendix Figure A4.

Overall, the results confirm we can trust the majority of estimates. The degree of omitted variables bias is likely to be low for noise pollution, green amenities within close distances (200 meters) and water within 50 meters. These coefficients tend to be adjusted downwards, yet largely remain within the confidence intervals of the estimates of the full model. For air pollution, trees between 50 and 100 meters and water over distances between 100 and 500 meters, the adjustment in the coefficient is much larger, indicating omitted variables are likely to influence these coefficients. In the following, the estimates for air pollution, trees (50-100 meter) and water (100-500 meter) must be therefore interpreted with caution. [16]

[16] This conclusion is corroborated by a test to address the multiple hypothesis problem – the Bonferroni correction. Since we consider the statistical inferences of a set of variables simultaneously, there is an increased risk of incorrectly rejecting a null hypothesis (type 1 errors). The Bonferroni correction proposes to control for this increased risk by reevaluating the desired significance levels using the formula α/m, where m refers to the number of hypothesis. Since

4.2. Main results: Nonlinear estimates

We now examine whether there is evidence for nonlinearity in the hedonic price schedule for environmental goods by adding polynomials to equation (1). We employ a consecutive approach. We first estimate marginal housing price associations by including second-order polynomials to equation (1) using a full set of controls. For each environmental good we test whether the second order polynomials do contribute significantly to the model. In case of a significant contribution, we add a third-order polynomial. This process is repeated to higher order polynomials until no significant contributions to the model are detected. Since higher order polynomials are hard to interpret, we visualize the marginal associations over the distribution for each of the environmental goods. We utilize similar scales on the y-axis for all panels in Figure 2 to demonstrate the relative magnitudes of the marginal effects for each of the environmental goods. In the computation of the marginal associations the values of the control covariates were averaged. Figure 2 presents the results of the preferred specification. Appendix Table A3 shows the regression table.

Figure 2 demonstrates clear differences in the optimal functional form for each environmental good. Nonlinearity in hedonic price schedules indicates that people are heterogenous in terms of their preferences (cq bid functions), while linear hedonic price schedules suggest that people have similar shaped bid functions. The figure displays linear hedonic price schedules for the indicators of air pollution and greenness at larger distances than 200 meters from a house. In contrast, we find nonlinear hedonic price schedules for noise pollution, water and greenness in direct proximity (within 200 meters). One interpretation of this difference in optimal functional forms is that households strongly sort themselves in terms of their preferences according to environmental characteristics that are directly noticeable (within 200 meters of a house). While beyond this distance households much less notice differences in the environmental goods leading to similar shaped bid functions.

What is the magnitude of our results? We start off by discussing the pollution indicators. We find a linear hedonic price schedules for airborne particulate matter ($PM_{2.5}$). Our results indicate that each μg/m^3 increase in $PM_{2.5}$ is associated with a decrease in residential property prices by 0.46%.[17] A caution here is that previous results using the omitted variables bias method by Oster (2019) suggests that there may be a bias for our estimates for $PM_{2.5}$. Moreover, the confidence interval increases sharply at the tails of the distribution.

Even with these caveats in mind, our results for particulate matter largely coincide with results found in the literature since 2005. Our results range from 0.3% to 0.5% in house prices per one-point μg/m^3 decrease in $PM_{2.5}$, while Chay & Greenstone (2005) and Bayer et al. (2009) find results in the range of 0.2% to 0.4%. These papers also obtain a linear functional form. Yet, these papers use PM_{10} as metric for air pollution instead of $PM_{2.5}$. Surprisingly, when we use PM_{10} as metric instead of $PM_{2.5}$, we find a mildly higher coefficient. For PM_{10}. each μg/m^3 increase is associated with a decrease in residential property prices by 0.5 to 0.6%.[18]

we consider 20 environmental variables simultaneously, we obtain a desired significance level of at least 0.0025 (0.05/20). In Appendix Figure A5, we show that the variables that must be interpreted with caution do not obtain this threshold of significance.

[17] Due to the problem of multicollinearity, we did not include $PM_{2.5}$ and NO_2 simultaneously in our regression analysis. Therefore we determined the willingness to pay for NO_2 by excluding $PM_{2,5}$ in equation (2). These results indicate that each μg/m^3 increase in NO_2 is associated with a decrease in residential property prices by 0.31%.

[18] These results are available upon request.

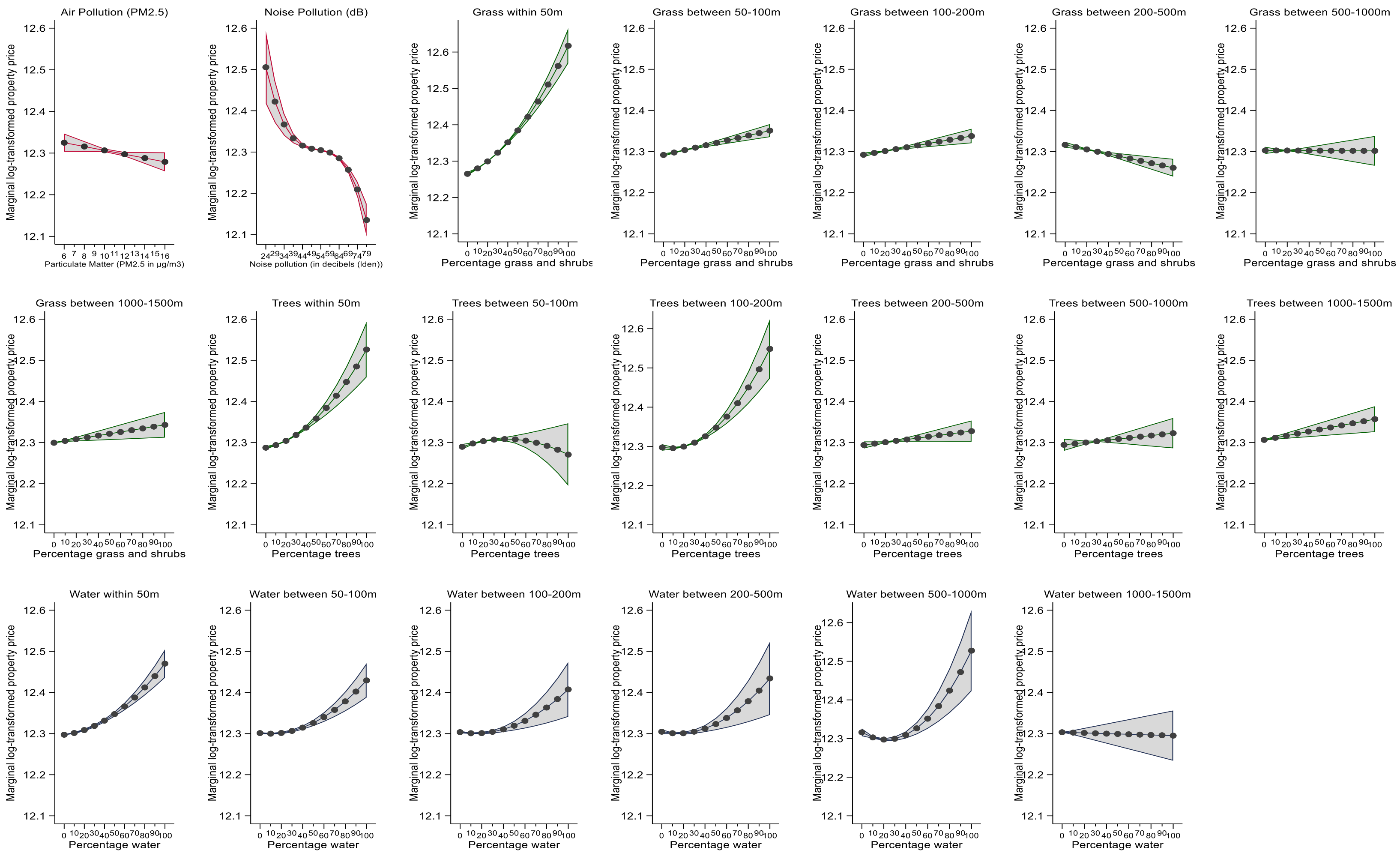


***Figure 2:** Allowing for nonlinearity in the hedonic price schedules for environmental goods*

Notes: Each panel shows the logarithmic residential price association of a marginal change in the environmental (dis)amenity of interest. The grey areas display the 95% confidence intervals.

In contrast to air pollution, the hedonic price schedule of noise pollution is strongly nonlinear. We find a cubic functional form, which suggests noise pollution is particularly valued at the tails of the distribution. Based on our estimates, a dB increase at 30 dB (70 dB) is associated with a 1.35% (0.73%) decrease in residential property prices. [19] At moderate levels of noise pollution (40-60dB) the curve is almost flat, as each dB within this range is associated with a decrease in prices of about 0.1%. This suggests that people strongly value areas that are more quiet than typical and that people strongly dislike very high noise levels.

Our estimates for noise pollution (0.1% to 1.5% per dB) are in line with the broad range found in the earlier literature: 0.08% to 2.22% per dB (Bateman et al.. 2001; Kopsch. 2016). However, our finding of a cubic functional form contrasts earlier literature. Earlier literature that allows for nonlinearity (e.g. Brandt and Maennig, 2011) find increasing marginal willingness to pay values per decibel at higher noise pollution levels. Yet, these studies do not find nonlinearities at lower decibel ranges (below 40 dB). The increasing coefficient at noise pollution levels above 70dB can be explained due to the fact that levels above this threshold are mostly caused by aircraft noise. The stated preferences meta-analysis by Bristow et al. (2015) and the revealed preferences meta-analysis by Kopsch (2016) find that households have a higher valuation for aircraft noise in comparison to other nodes. The relatively high willingness to pay at lower levels (below 40 dB) points to the conjecture that households strongly sort themselves within the lesser noise polluted areas

Next, we consider green scenery. The results shown in Figure 2 suggest that households particularly value greenness in direct proximity of a house (within 50 meters). In this range, the valuation is positive and quadratic, which suggests that households have an increasing valuation for additional amounts of green scenery. Dependent on the prevailing percentage of greenness, we find that a 10%-point increase in the percentage grass and shrubs (trees) is associated with an increase in residential property prices from 1 up to 4% (1 to 3%).[20] The modestly higher effect for grass and shrubs relative to trees, suggests that a group of housing consumers values a free view from a house higher than the cooling effect generated by trees in close proximity to a house (next to trees being an aesthetic amenity).

After a distance of 50 meters the coefficient size for green scenery decreases sharply, although there is a surprising pattern. According to our estimates, increasing the percentage trees by 10%-points between 100 and 200 meters is associated with a similar increase in property prices as within 50 meters (1-3%), but we estimate a much lower coefficient for trees between 50 and 100 meters. For trees between 50 and 100 meters, the relationship between trees and house prices is positive up to the threshold of 40% trees (of 0.8 to 0.1% per 10% point increase in trees). After

[19] We further investigated whether the willingness to pay for noise pollution depends on the number of insulation layers and/or the maintenance quality of a house. We therefore extended our previous strategy by interacting the hedonic price schedule for noise pollution with both characteristics. The results exhibited in Appendix Figure A3, confirm the idea that insulation and the maintenance quality matter in terms of the housing price relationship with noise pollution. In particular, especially within the range up to 50 decibels, the implied marginal willingness to pay for (less) noise pollution becomes stronger as the number of insulation layers (maintenance quality) increases.

[20] We did consider the hypothesis that households primarily value a direct view on green scenery instead of the percentage of green scenery around their house. We therefore included dummy variables indicating whether houses have a direct view on a) a forest b) a park and c) on water. The results, that are available upon request, indicated this addition primarily affects the coefficients of the willingness to pay measures for environmental amenities within 50 meters. Unsurprisingly, these coefficients are adjusted downwards, albeit slightly (less than 5%). Taking into account that households also value the percentage of green amenities, the willingness to pay for a direct view on a forest (water) is respectively 2% (4.8%). The willingness to pay for a view on a park is statistically insignificant.

this threshold, the relationship shows a decreasing pattern – albeit insignificant. This suggest that households, even though they value trees in close proximity of their house, are less alert about tree coverage beyond what they can observe from their homes. After a distance of 200 meters of a house, the correlation for trees is linear, almost negligible and statistically insignificant.

The housing price relationship of grass and shrubs also becomes much smaller at distances greater than 50 meters. Beyond 50 meters the housing price relations have a linear functional form. We find that each 10%-point increase in the percentage grass and shrubs between 50-100 meters (100-200 meters) is associated with an increase in residential property prices by 0.59% (0.44%). In the distances of 200 to 500 meters and 500 to 1000 meters, the effects for grass and shrubs are small and negative (-0.3 to -0.6% for each 10% increase in the percentage grass and shrubs). The latter negative results may be explained due to grass being a proxy for (intensive) farming. Intensive farming may bring about other negative externalities not being picked up by the pollution indicators.[21]

Our results on the effect of green scenery share few similarities, and considerable differences compared to earlier literature. Starting with the similarities, the distance to which the percentage tree scenery has a positive association with house prices is roughly similar. We find positive associations of tree coverage until 200 meters, similar to Saphores and Li (2012), while Sander et al. (2010) find positive associations of tree coverage until 250 meters.

Our results also have plenty of differences compared to earlier literature. First, the the distance to which the percentage grass and shrubs has a positive association with housing prices is different in the literature. While we find positive associations until 200 meters, the results in the literature are inconsistent. For example, Conway et al. (2010) find significant positive associations only within 60 to 90 meters, while Tsurumi and Managi (2015) do not find significant associations based on self-reported happiness data. Second, our results on the optimal functional form contrast findings in the literature. With the exception of Sander et al. (2010), the literature do not conduct tests to detect whether higher order polynomials contribute to a better fit of their model. Third, the coeffiicient size we obtain tend to be moderately higher than found in earlier literature. The difference is primarily determined by the reference point of the marginal change. To illustrate this, Saphores and Li (2012) report an association of 0.09% for a 1%-point increase in tree coverage within 200m. Adding up our effects until 200m gives an association of about 0.13% (between 0 and 10% coverage) and 0.58% (between 60 to 70% coverage) for a 1% tree coverage increase.

The housing price relationship with water does exhibit a much looser pattern of reducing returns to scale over space as the hedonic price schedules seems fairly similar over distance up to 1000m after which the association becomes insignificant. All hedonic price schedules up to 1000 meters for water have a positive quadratic optimal functional form. This indicates that households value increasing amounts of water. This may enable them to recreate on water beyond their direct proximity of their house. The negative effects of water (flood risks, potential breeding spot for mosquito's or rodents) do not seem to be valued highly.

[21] Another explanation is that our variables proxying for density (number of addresses, degree of urbanity) do not perfectly capture the full extent of density. In that case, the coefficients of the percentage grass (beyond 200 meters) may partially pick up a lack of density.

A closer inspection of the results shows that the marginal changes in the hedonic price schedule reveal large differences up to percentages of 50 percent. In this range, the highest associations are found within 50 meters of a house, as we find that a 10%-point increase in the percentage water is associated with an increase in residential property prices from 0.5% up to 1.5%. The associations for distances above 50 meters are somewhat smaller (0.2% up to 1%). Furthermore, the associations at larger distances become statistically insignificant at larger percentages of water (above 60%, due to few observations), while this is not the case for water in close proximity (within 50 and between 50 and 100 meters). For the latter intervals we find that a 10%-point increase in the percentage water above 60% is associated with an increase in residential property prices from 1.5% up to 3.0%. However, since earlier results suggests omitted variables are likely to impact these coefficient downwards, the coefficients within distances of 200 to 1000 meters for water must be interpreted with caution. Since there are no papers that estimate the willingness to pay for the percentage of water amenities around houses, our results cannot be compared to literature.[22]

4.3. *Sensitivity checks*

In this section, we perform a number of sensitivity checks to test the robustness of our nonlinear results. The obtained nonlinearities in the hedonic price schedules for various environmental (dis)amenities suggest sorting of preferences. Previous checks on the linear estimates using the method of Oster (2019) indicated that we should be cautious about omitted variable bias in our estimates for air pollution, trees (50-100 meter) and water (100-500 meter). At the same time, this test did not alter our findings suggesting that households particularly value environmental amenities in close proximity to their home that can be experienced directly. We included a large set of control variables in our baseline results. We now consider various other factors that may influence the hedonic price schedules. The results of our robustness checks are shown in Table 5.

As a first check, we determine whether the results may be driven by (omitted) housing characteristics. For example, it is possible that our baseline set of housing characteristics does not fully capture the (in)attractiveness of a house. It could be that the insulation and maintenance quality may not fully capture the way noise pollution is experienced within the house. We therefore include the annual electricity and gas use as an additional proxy for the exterior quality of a dwelling. Another concern is that our baseline categorization does not capture the full variety of dwelling types. This especially concerns the variety of detached houses (e.g. mansions, bungalows, farmhouses), which we now include as separate dummy variables.[23] Column (2) documents that the coefficients of the environmental (dis)amenities remain stable to the inclusion of these control variables.

Second, we investigate whether our results hold when we allow for differential trends in the willingness to pay. For instance, the willingness to pay for housing characteristics may be influenced by the time at which a dwelling is purchased. Differences in trends in the willingness to pay may also occur within the neighborhoods at which our spatial fixed effects are included in

[22] There are two papers that estimate the willingness to pay for the distance of a house to water: Cho et al. (2006) and Rouwendal et al. (2017). The results of these papers indicate that people are willing to pay for a closer distance of water to their house. The estimated relationship tend to be weak however, and in case of Rouwendal et al. (2017) already disappears after 30 to 40 meters. This paper primarily shows that households are willing to pay for a direct view on water from their house. In addition, our paper suggests that next to this direct view, people also value water at larger distances up to 1000 meters of their home, as this may enable them to recreate on water (e.g. using a boat).

[23] Appendix Table A2 provides the descriptive statistics of these variables.

the baseline specification. We therefore interact the baseline housing characteristics with a full set of time-period fixed effects. We do this too for the spatial fixed effects. The inclusion of these interaction variables again leaves our results largely unchanged as exhibited by column (3).

As a third sensitivity check, we examine whether the hedonic price schedule for environmental variables is related to dwelling types. Earlier results hint at a large heterogeneity in preferences for environmental variables. We check whether this heterogeneity of preferences is present among dwelling types by excluding apartments in our base sample. The results shown in column (4) indicate that the coefficients remain largely stable. Although the coefficients for environmental amenities in close proximity become slightly larger.

Next, we consider the possibility of overfitting. Our baseline specification includes a large set of variables that may be possibly related to environmental variables while simultaneously affecting residential property prices. Yet, these variables may be highly correlated due to spatial clustering. In this case, adding them to regression equation (2) may lead to a better predicting performance within the sample. However, in a new sample the added variables could induce an overcomplication of the 'true' relationship between variables. As a solution to prevent overfitting our model, we use a lasso methodology (Tibshirani, 1996).[24] The lasso excludes variables that contribute little to the model performance. Column (5) shows that the lasso does not substantially affect the coefficients of the environmental (dis)amenity variables.

Our final robustness check performs each of the former robustness check simultaneously. The results exhibited in column (6) are very close to the lasso robustness check in column (5) in combination with the exclusion of apartments in column (4). Again the coefficients of the environmental amenities in close proximity become slightly larger. Overall, Table 5 shows that the results are robust to other related determinants of housing prices and a number of econometric challenges.

Even though the addition of these observed determinants have little influence on our results, we emphasize that earlier results suggests that unobserved determinants seem to influence the results of air pollution, trees (50-100 meter) and water (100-500 meter). Unfortunately the Oster method is bounded in its ability to determine the degree of omitted variable bias when applied to nonlinear effects.[25] We argue that our previous cautions about the interpretation of the results for air pollution, trees (50-100 meter) and water (100-500 meter) therefore also applies to the set of nonlinear effects.

[24] We use the double-selection in combination with cross-validation to select the optimal value of the lasso penalty parameter. Details on the lasso methodology are provided in the Appendix section A3 Methods.
[25] Specifically, the method of Oster is not suited to perform the test simultaneously for the linear term and its higher order polynomials.

Table 5: *Sensitivity Checks*

	(1) Baseline	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	-0.00460**	-0.00663***	-0.00558**	-0.00313	-0.00545**	-0.00360*
	(0.00227)	(0.00226)	(0.00246)	(0.00205)	(0.00226)	(0.00197)
dB	-0.0662***	-0.0692***	-0.0671***	-0.0657***	-0.0634***	-0.0577***
	(0.0140)	(0.0146)	(0.0149)	(0.0150)	(0.0192)	(0.0196)
$(dB)^2$	0.00125***	0.00133***	0.00127***	0.00123***	0.00118***	0.000106***
	(0.000256)	(0.000265)	(0.000271)	(0.000277)	(0.000338)	(0.000307)
$(dB)^3$	-0.00000800***	-0.00000853***	-0.00000808***	-0.00000782***	-0.00000738***	-0.00000649***
	(0.00000155)	(0.00000160)	(0.00000164)	(0.00000169)	(0.00000203)	(0.00000213)
% Grass & shrubs within 50 meters house	0.00126***	0.00195***	0.00181***	0.00302***	0.00168***	0.00324***
	(0.000209)	(0.000209)	(0.000222)	(0.000199)	(0.000195)	(0.000178)
(% Grass & shrubs within 50 meters house)^2	0.0000226***	0.0000202***	0.0000152***	0.00000135	0.00000755*	0.00000672
	(0.00000407)	(0.00000411)	(0.00000435)	(0.00000386)	(0.00000425)	(0.00000537)
% Grass & shrubs between 50 and 100 meters house	0.000592***	0.000676***	0.000615***	0.000984***	0.000843***	0.00140***
	(0.0000981)	(0.0000995)	(0.000105)	(0.0000876)	(0.0000988)	(0.000111)
% Grass & shrubs between 100 and 200 meters house	0.000456***	0.000560***	0.000445***	0.000398***	0.000397***	0.000368***
	(0.000115)	(0.000118)	(0.000121)	(0.000103)	(0.000113)	(0.000123)
% Grass & shrubs between 200 and 500 meters house	-0.000559***	-0.000531***	-0.000652***	-0.00000916	-0.000751***	-0.000816***
	(0.000146)	(0.000147)	(0.000151)	(0.000128)	(0.000131)	(0.000178)
% Grass & shrubs between 500 and 1000 meters house	-0.0000108	-0.000192	-0.000276*	-0.000318**	-0.000165	-0.000216
	(0.000228)	(0.000164)	(0.000167)	(0.000145)	(0.000140)	(0.000149)
% Grass & shrubs between 1000 and 1500 meters house	0.000464	0.000770	0.000458	0.0000395	0.0000471	0.000770
	(0.000493)	(0.000500)	(0.000516)	(0.000451)	(0.000511)	(0.000691)
% Trees within 50 meters house	0.000444*	0.000704***	0.000680***	0.000598***	0.000706***	0.00123***
	(0.000232)	(0.000233)	(0.000246)	(0.000199)	(0.000223)	(0.000241)
(% Trees within 50 meters	0.0000194***	0.0000165***	0.0000139**	0.0000255***	0.00000881*	0.0000121**

house)²	(0.00000539)	(0.00000537)	(0.00000568)	(0.00000441)	(0.00000499)	(0.00000553)
% Trees between 50 and 100 meters house	0.000904*** (0.000306)	0.000807*** (0.000310)	0.00102*** (0.000318)	-0.000123 (0.000243)	0.00113*** (0.000290)	0.000749*** (0.000293)
(% Trees between 50 and 100 meters house)²	-0.0000109* (0.00000644)	-0.0000119* (0.00000647)	-0.0000118* (0.00000665)	0.0000142*** (0.00000480)	-0.0000158*** (0.00000589)	0.00000323 (0.00000596)
% Trees between 100 and 200 meters house	-0.000492 (0.000343)	-0.000620* (0.000349)	-0.000552 (0.000367)	-0.000230 (0.000295)	-0.000648* (0.000331)	-0.000304 (0.000350)
(% Trees between 100 and 200 meters house)²	0.0000300*** (0.00000663)	0.0000309*** (0.00000681)	0.0000306*** (0.00000711)	0.0000182*** (0.00000569)	0.0000336*** (0.00000664)	0.0000210*** (0.00000705)
% Trees between 200 and 500 meters house	0.000337* (0.000174)	0.0000633 (0.000163)	0.000223 (0.000168)	0.000391*** (0.000143)	0.000321** (0.000133)	0.000338** (0.000145)
% Trees between 500 and 1000 meters house	0.000283 (0.000262)	-0.000116 (0.000183)	-0.000250 (0.000193)	-0.0000279 (0.000166)	-0.000296 (0.000355)	-0.0000836 (0.000170)
% Trees between 1000 and 1500 meters house	0.000503 (0.000461)	0.000486 (0.000491)	0.000504 (0.000483)	0.000366 (0.000398)	0.000425 (0.000717)	0.0000311 (0.000464)
% Water within 50 meters house	0.000274** (0.000136)	0.000313** (0.000140)	0.000372** (0.000145)	0.000211* (0.000124)	0.000165 (0.000128)	0.000176 (0.000154)
(% Water within 50 meters house)²	0.0000145*** (0.00000283)	0.0000149*** (0.00000291)	0.0000141*** (0.00000304)	0.0000152*** (0.00000262)	0.0000153*** (0.00000287)	0.0000156*** (0.00000341)
% Water between 50-100 meters house	-0.000301** (0.000147)	-0.000239 (0.000151)	-0.000268* (0.000158)	-0.000360*** (0.000132)	-0.000250* (0.000144)	-0.000353** (0.000158)
(% Water between 50 and 100 meters house)²	0.0000158*** (0.00000324)	0.0000146*** (0.00000334)	0.0000157*** (0.00000349)	0.0000158*** (0.00000299)	0.0000127*** (0.00000331)	0.0000154*** (0.00000372)
% Water between 100 and 200 meters house	-0.000412** (0.000203)	-0.000409** (0.000205)	-0.000444** (0.000216)	-0.0000963 (0.000184)	-0.000246 (0.000185)	-0.000273 (0.000202)
(% Water between 100 and 200 meters house)²	0.0000145*** (0.00000496)	0.0000159*** (0.00000509)	0.0000169*** (0.00000528)	0.00000829* (0.00000447)	0.0000115** (0.00000470)	0.0000155*** (0.00000498)
% Water between 200 and	-0.000550*	-0.000533	-0.000373	-0.000773***	-0.000338	-0.000833***

500 meters house	(0.000325)	(0.000330)	(0.000344)	(0.000299)	(0.000264)	(0.000279)
(% Water between 200 and 500 meters house)^2	0.0000185*** (0.00000702)	0.0000189*** (0.00000718)	0.0000160** (0.00000737)	0.0000198*** (0.00000705)	0.0000173*** (0.00000587)	0.0000237*** (0.00000655)
% Water between 500 and 1000 meters house	-0.00170*** (0.000480)	-0.00141*** (0.000442)	-0.00131*** (0.000456)	-0.000992*** (0.000385)	-0.000939*** (0.000334)	-0.000802** (0.000377)
(% Water between 500 and 1000 meters house)^2	0.0000381*** (0.00000908)	0.0000357*** (0.00000883)	0.0000334*** (0.00000908)	0.0000262*** (0.00000764)	0.0000314*** (0.00000664)	0.0000259*** (0.00000733)
% Water between 1000 and 1500 meters house	0.000537 (0.000838)	0.000402 (0.000671)	0.000423 (0.000744)	0.000397 (0.000680)	0.000467 (0.000519)	0.000601 (0.00149)
Full set of control variables and fixed effects	Y	Y	Y	Y	Y	Y
Additional housing controls		Y				Y
Controls × time FE			Y			Y
Base sample excluding apartments				Y		Y
Lasso					Y	Y
Observations	146,823	146,823	146,823	108,295	146,823	108,295
R-squared	0.817	0.819	0.826	0.842		

Notes: This table performs multiple sensitivity checks to determine the robustness of the statistical association between environmental variables and log-transformed residential property prices. Baseline results of Figure 2 reported in column (1). A description of the environmental variables is listed in Table 2. Each of the reported results in columns (1) to (6) include time fixed effects, neighborhood fixed effects and a full set of control covariates (housing characteristics, producer and consumer amenities, demographic characteristics and socio-economic characteristics). An overview of the control covariates is provided in Appendix Table A1. For a description of the environmental variables, see Table 2. Standard errors clustered on 1 by 1km spatial grids are reported in parentheses. A description of the lasso methodology (columns 5, 6) is listed in Appendix section Methods. Statistical significance denoted by * p < 0.10, ** p < 0.05, *** p < 0.01.

4.4. *Discussion: Do people internalize the health effects of environmental disamenities?*

In this section, we infer the health costs of air and noise pollution under a set of assumptions, and then compare them to our estimates which are interpreted as causal, only for this exercise. We present a back-on-the-envelope calculation based on a number of papers that estimate the health effects of the exposure of people to environmental goods using similar metrics as we do. Moreover, we focus on the effects on life expectancy. which we are able to translate into quality-adjusted life years (QALYs) – the accepted metric to define health effects as welfare costs (Weinstein et al., 2009).

There are two papers that estimate the life-expectancy effects of peoples' exposure to particulate matter. We assume that the findings of these papers can be applied in the Netherlands. The results of the first paper by Ebenstein et al. (2017) indicate that a (permanent) 1 $\mu g/m^3$ increase in PM_{10} leads to a decline in life expectancy by 0.064 years. This corresponds to a decline of about 0.0008 life years per year per person. The second paper by Deryugina et al. (2019) shows that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ leads to a decline of 3 days per million people per year. This corresponds to a life expectancy decline of about 0.0011 year per year per person. We make five assumptions to translate the effects found in the health literature to social welfare costs relevant in the Netherlands. First, we assume the value of an average QALY of 80.000 euros. Second, we assume each year of additional life expectancy corresponds to a less than proportional (0.82) QALY (based on Versteegh et al.. 2019). Third. the discount rate is 2.25%. Fourth. the average price for a residential property is 245,000 euros. Fifth. the average household size is 2.2 persons (CBS. 2022).

When we compare the health costs to our estimated associations, we find that people only seem to partially internalize the health costs of $PM_{2.5}$. Using the assumptions above, a 1 $\mu g/m^3$ increase in PM_{10} ($PM_{2.5}$) is associated with a social costs of 72 to 94 euros in terms of QALYs per person per year. Our estimates of the willingness to pay for a 1 $\mu g/m^3$ increase in $PM_{2.5}$ translate to about 13 euros per person per year (based on an effect estimate of -0.46% per $\mu g/m^3$). This corresponds to less than 20% of the social costs of $PM_{2.5}$.

We performed a similar analysis with regards to noise pollution. This time we used the EU Handbook for environmental prices to infer the size of the health effects (de Bruyn et al, 2016). According to the handbook, there is a monotonic increase in the health effects of noise pollution The detrimental health effects start above 50dB, where each dB increase is associated with a health cost of 22 euro per person per year. The health effects increase to around 100 euros per dB per person per year in the range above 65dB for road traffic. The health effects of aviation noise is the most detrimental at over 180 euro per dB in the range above 65dB.

Similar to air pollution ($PM_{2,5}$), we find that people only partially internalize the health costs of noise pollution (dB, Lden). Our estimates of the willingness to pay for noise pollution in the range of 50 to 79 dB indicate that each dB increase is associated with an increasing decline in residential property prices of 0.1% to 1.5%. Using the five assumptions stated above, this translates to 4 to over 40 euros per person per year. Our results suggest that people internalize less than 10% of the social costs in the range up to 60 dB. In the range above 70 dB people internalize more than 30% of the social costs.

There are a number of possible, interrelated, explanations for these findings. First, people only internalize private costs. since the personal health care payments are capped in the Netherlands (above this cap the costs are reimbursed by the health insurance company). Second, people have incomplete information about the health effects of the exposure to environmental goods. That is, people do not immediately notice slight differences in the exposure of environmental disamenities, even though in the long run, they are likely to experience different health effects.

5. Conclusions

This study examines the association of environmental goods with house prices. While employing a dataset with a large set of controls, we use hedonic pricing as a method to infer the association of air pollution, noise pollution, green scenery, and water scenery with housing prices in the Netherlands. We have two main findings.

First, we find that the inclusion of noise pollution and tree coverage has a substantial impact on the coefficient for air pollution. For example, our linear estimate (without controls for consumer and producer amenities and neighborhood characteristics) for the effect of air quality ($PM_{2.5}$) on house prices of -1.45% per μg per m^3, goes down by around one third to -0.98% when controlling for the amount of tree coverage around the house. Adding noise (decibels) to the regression, lowers the air quality estimate by approximatively 25% to -0.74%, indicating substantial overestimation in the initial regression. When all controls are included, we find that each μg/m^3 increase in $PM_{2,5}$ is associated with a decrease in residential property prices by 0.46%. Due to these coefficient changes, the test by Oster(2019) suggests unobserved covariates are likely to bias the results.

Second, according to our estimates households seem to particularly value noise pollution and environmental amenities within close proximity of their house. The hedonic price schedules for these environmental goods have a nonlinear functional form. Our findings suggests that the strongest housing price associations are found for environmental amenities within 50 meters. Dependent on the prevailing percentage of green or water, we find that a 10%-point increase in the percentage grass and shrubs (trees, water) is associated with an increase in residential property prices from 1 up to 4% (1 to 3%). In the distance between 50 meters and 200 meters the willingness to pay for green decreases sharply to about 0.5 % for each 10%-point increase. After 200 meters the willingness to pay for green becomes statistically insignificant. In contrast, the willingness to pay for water remains strong and quadratic to a distance of 1 kilometer, as each 10%-point increase is associated with a surge in residential prices by 0.2 to 1.0%.

We find a cubic functional form in the hedonic price schedule of noise pollution, which suggests that households primarily value less noise at the tails of the distribution (within the range of 20 to 40 dB and 60 to 80 dB). At these tails, each one dB increase is associated with a decrease in residential property prices by 0.8 to 1.5%. At the range of moderate noise pollution levels (40 to 60 dB), we find a small willingness to pay for less noise (0.1% per dB).

Our paper contributes to the literature that uses hedonic pricing to investigate the willingness to pay for environmental goods. Aside from the importance of interrelated variables and nonlinearities, we question whether the inferred willingness to pay effects can be used as welfare effects in costs-benefit analyses. A number of studies show that the health effects of air and noise pollution are much higher than the valuation of households in terms of housing prices. This suggests that people only partially internalize the health effects of environmental goods.

Novel research could incorporate these lessons and apply them in quasi experimental to provide causal estimates of the effect of environmental (dis)amenities on house prices. This could benefit project evaluation aimed at reducing disamenities and increasing the attractiveness of public space by providing more green and water. Novel research could also extent the investigation of health effects into other environmental goods in terms of changes in peoples life expectancy. The (small) internalization of the health effects of environmental variables may be a reason for policy intervention.

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Appendix

The Appendix proceeds as follows. Appendix section A1 provides detailed information about the data, contains additional figures, and lists a number of Tables. An overview of the hedonic price method is postulated in Appendix section A2. Appendix section A3 describes the lasso methodology in detail.

A1. Data appendix

1. ***Figures***

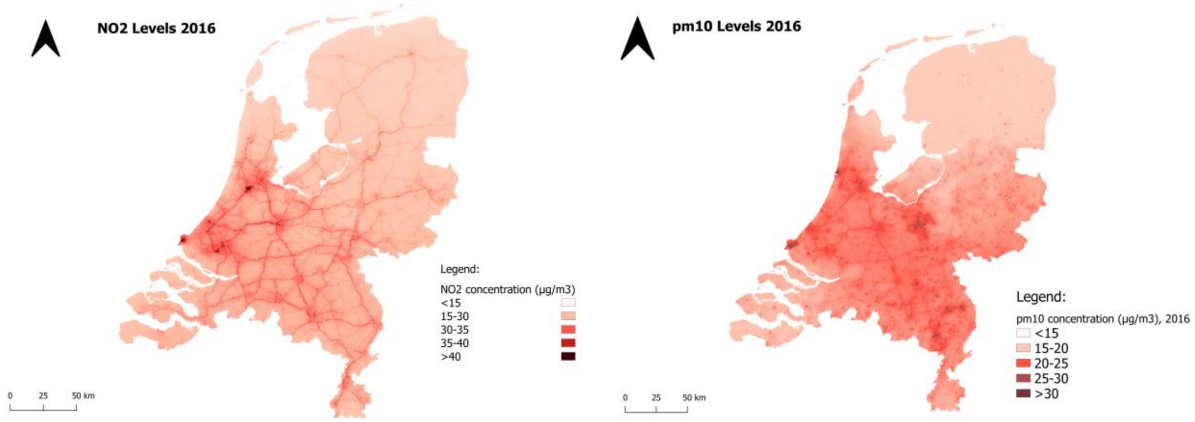

Figure A1: *Air pollution concentrations of NO_2 and PM_{10} in the Netherlands during 2016*

Figure A2: *Green scenery (trees, grass and shrubs) and water scenery in the Netherlands during 2016*

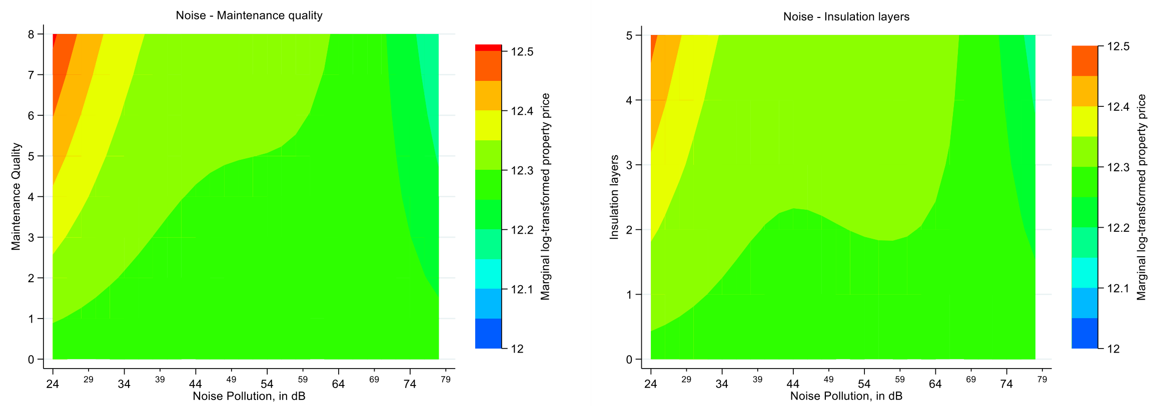

Figure A3: *Does the willingness to pay for noise pollution depend on the a) maintenance quality and b) the number of insulation layers of a house?*

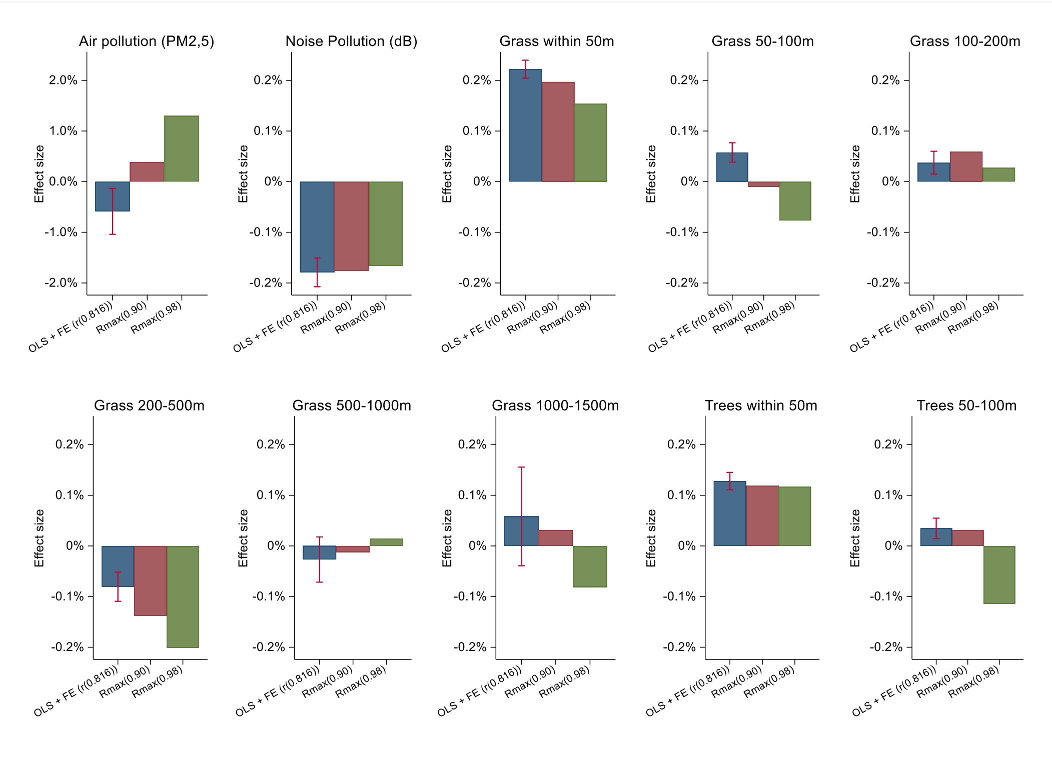

Figure A4.1: *Can we trust our linear baseline estimates? An indication of the degree of omitted variable bias*

Notes: The blue bars indicate the baseline results exhibited in Table 4 column (5). The red and the green bar display the suggested beta coefficient using the method by Oster (2019), using a R^2max of 0.90 and 0.98, respectively.

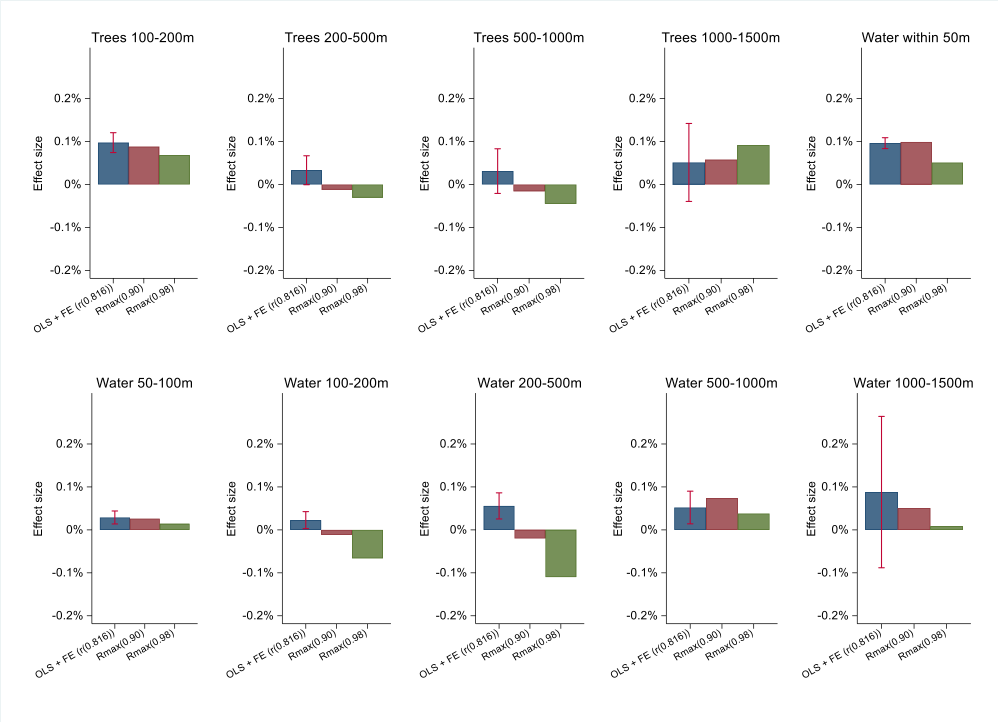

Figure A4.2: *Can we trust our linear baseline estimates? An indication of the degree of omitted variable bias*

Notes: The blue bars indicate the baseline results exhibited in Table 4 column (5). The red and the green bar display the suggested beta coefficient using the method by Oster (2019), using a R^2max of 0.90 and 0.98, respectively.

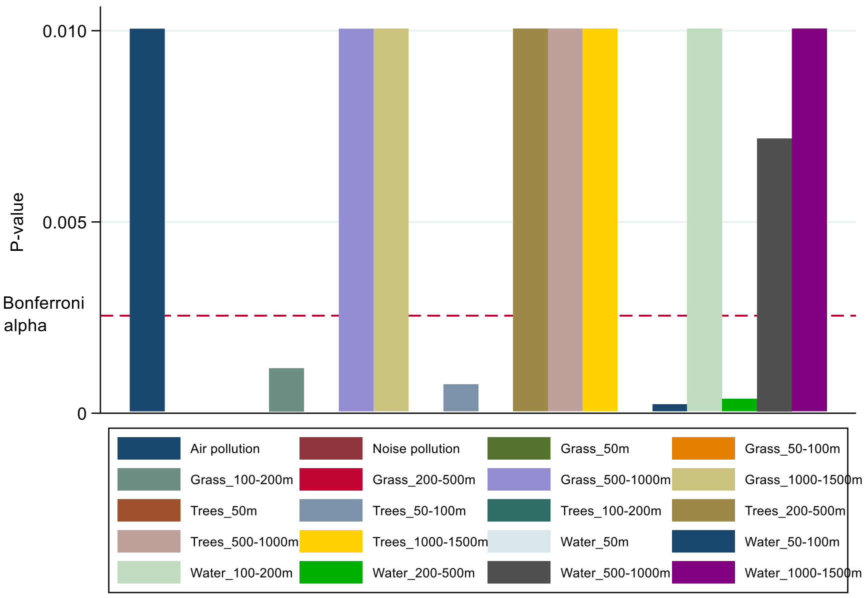

Figure A5: *Addressing the multiple hypothesis problem – using the Bonferroni correction method*

Notes: In this figure, we consider whether the null hypothesis of the effect being equal to 0 is rejected correctly due to the multiple hypothesis problem: the increased risk of Type 1 errors. The figure displays the p-values of the linear estimation results (Table 4 column 5). Variables with p-values above 0.01 are capped at 0.01, variables with p-values <0.001 are not visible. The suggested Bonferroni alpha is $\alpha/_{m} = {0.05}/_{20} = 0.0025$, which is shown by the red dashed line. Overall, the variables air pollution, and the environmental amenities at larger distances than 500 meter fail to reach the Bonferroni alpha value (likewise the variables water between 100 and 200 meters and trees between 20 and 500 meters).

2. *Tables*

Table A1: *Selection Criteria Residential Property Data*

Selection Criteria	Number of observations
1. Initial dataset (2016)	192,319
2. Discard observations in case dwelling has no permanent residential use (building ground, garage box, mobile home or 2nd recreational home)	188,887
3. Discard observations in case dwelling is bought as... *(i)* investment, *(ii)* partially sublet, *(iii)* sold in an auction	188,069
4. Discard observations with missing residential characteristics (see Table 3, e.g. unknown living space or transaction price)	181,468
5. Discard observations with unreliable characteristics (coding errors in residential characteristics, e.g. living space larger than parcel space)	173,239
6. Discard observations with ground lease	158,637
7. Discard postal codes with less than 20 transactions (2016)	148,306
8. Discard potential outliers (lowest 0.5 percentile, and highest 99.5 percentile of transaction prices)	146,823

Table A2*: Neighborhood Statistics on (Dis)amenities*

	Mean	Standard deviation	Description
Producer amenities			
...Addresses	1,849.29	1,502.32	Average number addresses per km^2
...Urbanism	2.68	1.31	Degree of urbanism, ranging from 1 (low) to 5 (high)
...Houses	1,668.65	1,383.08	Number of houses
...Sector A	3.46	9.67	Employees in sector A (Agriculture, forestry, fishing, and hunting)
...Sector B-F	38.10	37.51	Employees in sector B-F (Industry and energy)
...Sector G-I	57.38	68.49	Employees in sector G-I (Trade and catering)
...Sector H-J	23.76	24.60	Employees in sector H-J (Transport, information and communication)
...Sector K-L	27.17	30.37	Employees in sector K-L (Financial services)
...Sector M-N	80.46	85.92	Employees in sector M-N (Business services)
...Sector R-U	39.28	39.90	Employees in sector R-U (Culture, recreation, other services)
...Highway ramp	1.73	0.98	Road distance to closest highway ramp
...Rail station	3.43	3.75	Linear distance to closest railway station
Consumer amenities			
...Cultural heritage	4.34	3.80	Linear distance to closest cultural heritage area
...General practioner	0.90	0.72	Closest distance to general practioner
...Pharmacist	1.11	0.98	Closest distance to pharmacist
...Hospitals	4.41	3.69	Closest distance to hospital
......within 5km	1.24	1.36	Number of hospitals within 5km
......within 10km	1.85	2.12	Number of hospitals between 5 and 10km
......within 20km	6.06	5.26	Number of hospitals between 10 and 20km
...Supermarkets	0.82	0.70	Closest distance to supermarket
......within 1km	1.91	1.82	Number of supermarkets within 1km
......within 3km	8.40	9.68	Number of supermarkets between 1 and 3km
......within 5km	10.27	12.34	Number of supermarkets between 3 and 5km
...Department stores	2.40	2.21	Closest distance to department store
......within 5km	2.39	2.44	Number of department stores within 5km
......within 10km	3.98	3.54	Number of department stores between 5 and 10km
......within 20km	12.79	8.58	Number of department stores between 10 and 20km
...Cafes	1.13	1.04	Closest distance to café
......within 1km	4.76	11.71	Number of cafes stores within 1km
......within 3km	24.62	55.35	Number of cafes stores between 1 and 3km
......within 5km	25.63	54.61	Number of cafes stores between 3 and 5km
...Cafeteria	0.74	0.75	Closest distance to cafeteria
......within 1km	6.71	12.39	Number of cafeteria within 1km
......within 3km	34.32	61.11	Number of cafeteria between 1 and 3km
......within 5km	37.54	65.40	Number of cafeteria between 3 and 5km
...Restaurants	0.76	0.64	Closest distance to restaurants
......within 1km	9.33	22.31	Number of restaurants within 1km
......within 3km	48.05	109.17	Number of restaurants between 1 and 3km
......within 5km	50.66	108.59	Number of restaurants between 3 and 5km
...Hotels	2.37	1.87	Closest distance to hotels
......within 5km	11.53	39.17	Number of hotels within 5km
......within 10km	14.75	30.95	Number of hotels between 5 and 10km
......within 20km	50.88	69.98	Number of hotels between 10 and 20km
...Fire-fighting brigade	2.04	1.19	Closest distance to fire-fighting brigade
...Swimming pool	3.07	2.40	Closest distance to swimming pool

…Ice-skating lane	17.42	15.10	Closest distance to ice-skating lane
…Library	1.80	1.45	Closest distance to library
…Cinemas	5.92	5.21	Closest distance to cinema
……within 5km	1.25	1.92	Number of cinemas within 5km
……within 10km	1.37	1.91	Number of cinemas between 5 and 10km
……within 20km	4.39	3.96	Number of cinemas between 10 and 20km
…Sauna	7.93	5.67	Closest distance to sauna
…Tanning bed	3.85	4.88	Closest distance to tanning bed facility
…Amusement parks	5.89	4.55	Closest distance to Amusement park, zoo and indoor playgrounds
……within 10km	2.25	1.84	Number of Amusement park, zoo and indoor playgrounds within 10km
……within 20km	4.37	3.27	Number of Amusement park, zoo and indoor playgrounds between 10 and 20km
……within 50km	24.88	9.86	Number of Amusement park, zoo and indoor playgrounds between 20 and 50km
…Music venues	4.50	4.15	Closest distance to Amusement park, zoo and indoor playgrounds
……within 5km	2.55	4.52	Number of music venues within 5km
……within 10km	2.92	4.44	Number of music venues between 5 and 10km
……within 20km	9.04	9.62	Number of music venues between 10 and 20km
…Child cares	0.74	0.74	Closest distance to child cares
……within 1km	2.61	2.89	Number of child cares within 1km
……within 3km	12.69	15.36	Number of child cares between 1 and 3km
……within 5km	16.35	19.03	Number of child cares between 3 and 5km
…Extracurricular child cares	0.73	0.70	Closest distance to extracurricular child cares
……within 1km	2.33	1.94	Number of extracurricular child cares within 1km
……within 3km	11.31	11.21	Number of extracurricular child cares between 1 and 3km
……within 5km	15.15	15.99	Number of extracurricular child cares between 3 and 5km
…Elementary schools	0.63	0.40	Closest distance to elementary school
……within 1km	2.05	1.29	Number of elementary schools within 1km
……within 3km	9.09	8.16	Number of elementary schools between 1 and 3km
……within 5km	12.20	11.80	Number of elementary schools between 3 and 5km
…High schools	2.27	2.18	Closest distance to high schools (all levels)
……within 3km	3.50	3.84	Number of high schools (all levels) within 3km
……within 5km	3.40	4.30	Number of high schools (all levels) between 3 and 5km
……within 10km	9.34	9.84	Number of high schools (all levels) between 5 and 10km
…High schools (vmbo)	2.46	2.24	Closest distance to high schools (vmbo)
……within 3km	2.37	2.47	Number of high schools (vmbo) within 3km
……within 5km	2.35	2.97	Number of high schools (vmbo) between 3 and 5km
……within 10km	6.73	7.14	Number of high schools (vmbo) between 5 and 10km
…High schools (havo/vwo)	2.87	2.69	Closest distance to high schools (havo/vwo)
……within 3km	1.92	2.22	Number of high schools (havo/vwo) within 3km
……within 5km	1.85	2.46	Number of high schools (havo/vwo) between 3 and 5km
……within 10km	5.03	5.33	Number of high schools (havo/vwo) between 5 and 10km
Demographic variables			
…Female	50.56	1.99	Percentage of inhabitants female
…0-14 years	16.36	4.57	Percentage inhabitants 0-14 year old
…15-24 years	11.96	4.20	
…25-44 years	24.93	7.14	Percentage inhabitants 25-44 year old
…45-64 years	28.19	5.20	Percentage inhabitants 45-64 year old
… 65 and older	18.54	8.20	Percentage inhabitants 65 years and older
…non-married	47.44	9.55	Percentage inhabitants non-married
…married	39.82	8.88	Percentage inhabitants married
…divorced	7.55	2.35	Percentage inhabitants divorced
…widowed	5.16	3.07	Percentage inhabitants widowed
…Infants per 1000 inhabitants	9.92	3.86	Number of infants born per 1000 inhabitants
…Deaths per 1000 inhabitants	8.75	7.45	Number of deaths per 1000 inhabitants
… Inhabitants per km^2	5,221.56	3,961.71	Number of inhabitants per km2
…One-person households	35.58	13.63	Percentage one-person households
…Households w/o children	29.83	6.30	Percentage households without children
…Households with children	34.58	11.41	Percentage households with children
…Household size	2.21	0.35	Average number of persons in households
…Western immigrants	9.64	4.67	Percentage western immigrants
…Non-western immigrants	10.07	9.71	percentage non-western immigrants
Housing stock variables			
…Owner-occupied	61.32	18.00	Percentage owner-occupied dwellings
…Rent	37.58	17.61	Percentage dwellings for rent
…Social rent	25.23	16.64	Percentage dwellings owned/rented out by corporations
…Single-family housing	68.35	26.96	Percentage single-family households
…Multiple family housing	31.60	26.93	Percentage multiple family housing
…Non-vacant	95.77	4.41	Percentage used dwellings, cq lived in

Socio-economic variables			
…Disability benefits	4.23	1.87	Percentage persons with disability benefits
…Unemployment benefits	2.34	0.64	Percentage persons with unemployment benefits
…Social assistance benefits	2.55	2.05	Percentage persons with social assistance benefits
…Elderly benefits	18.06	8.08	Percentage persons with elderly benefits
…Actives	59.58	6.57	Percentage inhabitants active on labor market, aged 15-75y
…Household income	36.44	14.53	Average household income
…High income households	21.77	11.44	Percentage households in highest 20% gross income distribution
…Low income households	6.69	4.37	Percentage households in lowest 40% gross income distribution
Robustness variables			
			Dummy variable that equals one if the residence is a (detached) house and…
…Canal house	0.0011	0.034	Located in front of a canal
…Mansion	0.045	0.21	Located detached and categorized as mansion
…Farmhouse	0.011	0.10	Located detached and categorized as farmhouse
…Bungalow	0.025	0.16	Located detached and categorized as bungalow
…Villa	0.028	0.16	Located detached and categorized as villa
…Country house	0.00047	0.069	Located detached and categorized as country house
…Annual electricity use	2,975.85	560.54	The annual electricity use (kWh) for dwelling *i*, based on previous year
…Annual gas use	1,385.74	395.89	The annual gas use (m^3) for dwelling *i*, based on previous year
…District heating	49.30	11.86	Percentage dwellings with district heating

Notes: The table reports the weighted averages and standard deviations on (dis)amenities in local neighborhoods based on the number of observations (146,823). The variables are sorted into four main vectors (i) producer and consumer amenities, (ii) demographic characteristics, (iii) socio-economics characteristics, and (iv) robustness characteristics. All of the data are drawn from Statistics Netherlands (Wijk-en buurtkaart 2016), except for the data on cultural heritage and the data on a number of spatial characteristics. The data on cultural heritage (distance) is drawn from the Department of Cultural Heritage (in Dutch: Rijksdienst voor Cultureel Erfgoed. RCE). They refer to protected cityscapes and townscapes, which are areas in a cities and villages with a special cultural-historical character. The protected town and village views were built or laid out before the Second World War. There are currently 472 of these protected areas in the Netherlands. Distances are measured in kilometers.

Table A3: *Testing for Nonlinearity in the Willingness to Pay for Environmental Variables*

	(1)	(2)	(3)	(4) Optimal functional form	(5) Functional form
$PM_{2.5}$	0.00695	-0.00444**	-0.00460**	-0.00460**	Linear
	(0.0182)	(0.00226)	(0.00227)	(0.00227)	
$(PM_{2.5})^2$	-0.000531				F(0.40)
	(0.000837)				P(0.53)
dB	0.00574***	-0.0657***	-0.106	-0.0662***	Cubic
	(0.00179)	(0.0140)	(0.0672)	(0.0140)	
$(dB)^2$	-0.0000663***	0.00125***	0.00237	0.00125***	F(16.79)
	(0.0000162)	(0.000256)	(0.00189)	(0.000256)	P(0.00)
$(dB)^3$		-0.00000795***	-0.0000219	-0.00000800***	F(26.51)
		(0.00000154)	(0.0000234)	(0.00000155)	P(0.00)
$(dB)^4$			6.41e-08		F(0.35)
			(0.000000108)		P(0.55)
% Grass & shrubs within 50 meters house	0.00136***	0.00113***	0.00126***	0.00126***	Quadratic
	(0.000220)	(0.000415)	(0.000209)	(0.000209)	
(% Grass & shrubs within 50 meters house)^2	0.0000206***	0.0000282*	0.0000226***	0.0000226***	F(21.51)
	(0.00000445)	(0.0000166)	(0.00000407)	(0.00000407)	P(0.00)
(% Grass & shrubs within 50 meters		-6.43e-08			F(0.11)
		(0.000000194)			P(0.74)

house)^3					
% Grass & shrubs between 50 and 100 meters house	0.000484** (0.000219)	0.000595*** (0.0000980)	0.000592*** (0.0000981)	0.000592*** (0.0000981)	Linear
(% Grass & shrubs between 50 and 100 meters house)^2	0.00000247 (0.00000427)				F(0.34) P(0.56)
% Grass & shrubs between 100 and 200 meters house	0.000136 (0.000314)	0.000452*** (0.000114)	0.000456*** (0.000115)	0.000456*** (0.000115)	Linear
(% Grass & shrubs between 100 and 200 meters house)^2	0.00000560 (0.00000539)				F(1.08) P(0.30)
% Grass & shrubs between 200 and 500 meters house	-0.000836* (0.000466)	-0.000528*** (0.000145)	-0.000557*** (0.000146)	-0.000559*** (0.000146)	Linear
(% Grass & shrubs between 200 and 500 meters house)^2	0.00000410 (0.00000713)				F(0.33) P(0.57)
% Grass & shrubs between 500 and 1000 meters house	-0.000294 (0.000537)	0.0000231 (0.000228)	-0.00000850 (0.000228)	-0.0000108 (0.000228)	Linear
(% Grass & shrubs between 500 and 1000 meters house)^2	0.00000342 (0.00000883)				F(0.15) P(0.70)
% Grass & shrubs between 1000 and 1500 meters house	-0.000445 (0.000790)	0.000491 (0.000494)	0.000467 (0.000493)	0.000464 (0.000493)	Linear
(% Grass & shrubs between 1000 and 1500 meters house)^2	0.00000435 (0.00000497)				F(0.93) P(0.33)
% Trees within 50 meters house	0.000469** (0.000233)	0.000928** (0.000455)	0.000445* (0.000232)	0.000444* (0.000232)	Quadratic
(% Trees within 50 meters house)^2	0.0000193*** (0.00000539)	-0.00000196 (0.0000205)	0.0000194*** (0.00000539)	0.0000194*** (0.00000539)	F(12.78) P(0.00)
(% Trees within 50 meters house)^3		0.000000255 (0.000000272)			F(0.88) P(0.35)
% Trees between 50 and 100 meters house	0.000888*** (0.000307)	0.00184*** (0.000673)	0.000903*** (0.000306)	0.000904*** (0.000306)	Quadratic
(% Trees between 50 and 100 meters house)^2	-0.0000104 (0.00000643)	-0.0000472* (0.0000276)	-0.0000109* (0.00000643)	-0.0000109* (0.00000644)	F(2.87) P(0.09)
(% Trees between 50 and 100 meters house)^3		0.000000403 (0.000000342)			F(1.41) P(0.24)
% Trees between 100 and 200 meters house	-0.000499 (0.000352)	-0.000454 (0.000780)	-0.000491 (0.000343)	-0.000492 (0.000343)	Quadratic
(% Trees between 100 and 200 meters house)^2	0.0000302*** (0.00000697)	0.0000305 (0.0000293)	0.0000300*** (0.00000663)	0.0000300*** (0.00000663)	F(18.82) P(0.00)

(% Trees between 100 and 200 meters house)³		-3.72e-08 (0.000000338)			F(0.01) P(0.91)
% Trees between 200 and 500 meters house	0.000239 (0.000545)	0.000333* (0.000174)	0.000337* (0.000174)	0.000337* (0.000174)	Linear
(% Trees between 200 and 500 meters house)²	0.00000205 (0.00000916)				F(0.05) P(0.82)
% Trees between 500 and 1000 meters house	0.000563 (0.000685)	0.000244 (0.000262)	0.000284 (0.000262)	0.000283 (0.000262)	Linear
(% Trees between 500 and 1000 meters house)²	-0.00000492 (0.00000977)				F(0.25) P(0.61)
% Trees between 1000 and 1500 meters house	0.000775 (0.000512)	0.000501 (0.000460)	0.000504 (0.000461)	0.000503 (0.000461)	Linear
(% Trees between 1000 and 1500 meters house)²	-0.0000178 (0.0000418)				F(0.18) P(0.67)
% Water within 50 meters house	0.000275** (0.000136)	-0.000317 (0.000247)	0.000275** (0.000136)	0.000274** (0.000136)	Quadratic
(% Water within 50 meters house)²	0.0000145*** (0.00000283)	0.0000421*** (0.0000106)	0.0000145*** (0.00000283)	0.0000145*** (0.00000283)	F(23.91) P(0.00)
(% Water within 50 meters house)³		-0.000000293 (0.00000212)			F(0.85) P(0.36)
% Water between 50-100 meters house	-0.000300** (0.000147)	-0.000480** (0.000236)	-0.000301** (0.000147)	-0.000301** (0.000147)	Quadratic
(% Water between 50 and 100 meters house)²	0.0000158*** (0.00000324)	0.0000282*** (0.0000107)	0.0000158*** (0.00000324)	0.0000158*** (0.00000324)	F(23.91) P(0.00)
(% Water between 50 and 100 meters house)³		-0.000000161 (0.000000129)			F(1.56) P(0.21)
% Water between 100 and 200 meters house	-0.000405** (0.000202)	0.000164 (0.000311)	-0.000413** (0.000203)	-0.000412** (0.000203)	Quadratic
(% Water between 100 and 200 meters house)²	0.0000145*** (0.00000495)	-0.0000198 (0.0000148)	0.0000145*** (0.00000496)	0.0000145*** (0.00000496)	F(8.52) P(0.00)
(% Water between 100 and 200 meters house)³		0.000000253 (0.000000198)			F(1.66) P(0.19)
% Water between 200 and 500 meters house	-0.000468 (0.000327)	-0.00146*** (0.000533)	-0.000550* (0.000325)	-0.000550* (0.000325)	Quadratic
(% Water between 200 and 500 meters house)²	0.0000173** (0.00000702)	0.0000609*** (0.0000226)	0.0000185*** (0.00000702)	0.0000185*** (0.00000702)	F(6.09) P(0.01)
(% Water between 200 and 500 meters house)³		-0.000000256 (0.000000278)			F(1.05) P(0.31)
% Water between 500 and 1000 meters house	-0.00145*** (0.000478)	-0.00331*** (0.000772)	-0.00170*** (0.000480)	-0.00170*** (0.000480)	Quadratic
(% Water between 500 and 1000 meters house)²	0.0000341*** (0.00000896)	0.000104*** (0.0000274)	0.0000381*** (0.00000909)	0.0000381*** (0.00000908)	F(14.48) P(0.00)

(% Water between 500 and 1000 meters house)^3		-0.000000353 (0.000000295)			F(1.84) P(0.18)
(% Water between 1000 and 1500 meters house)^2	0.000617 (0.00169)	0.0004169 (0.000949)	0.000338 (0.000939)	0.000537 (0.000838)	Linear
(% Water between 1000 and 1500 meters house)^3	-0.0000819 (0.000288)				F(0.29) P(0.66)
Full set of control variables and fixed effects	Y	Y	Y	Y	

Notes: This table tests whether the statistical association between environmental variables and log-transformed residential property prices is nonlinear. Column (5) reports the results of Ramsey-reset tests to indicate whether the higher-order terms add a significant contribution to the model. The reported F-values correspond to regression results in column (1), (2) and (3). For example, the F-value of the (dB)^2 polynomial is reported in the same row in column (5). The Ramsey-resets tests of the third and fourth-order polynomials are conducted under the assumption that the previous model comprising the second respectively third order polynomials are correctly specified. All regressions include the full set of control covariates and fixed effects. For an overview of the control variables, see Appendix Table A1. All regressions include over 4/5th of the residential property transactions in the Netherlands during the year 2016. The number of observations is 146,823. For a description of the environmental variables, see Table 2. Standard errors clustered on 1 by 1km spatial grids are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

A2. Hedonic price method

The main goal of this paper is to infer the economic value of environmental goods. In the absense of a market for environmental (dis)amenities, we use the hedonic price method. Originally coined by Rosen (1974), the hedonic price method postulates the value of a differentiated good to be described by a vector of its components $P_i = P(x_{i1}, x_{i2}, \dots, x_{in})$. In the residential property market, the components comprise structural characteristics (e.g. parcel size), neighborhood characteristics (e.g. the average household income), spatial characteristics (e.g. distance to (dis)amenities), and environmental characteristics (e.g. the air pollution concentration $PM_{2.5}$).

Under the assumption of competitive markets, we can expect households to maximize their utility $U = u(C, X)$ subject to their budget constraints $C = I - P(X)$, where C refers to consumption and I to household income. In equilibrium the following condition must hold for each of the housing components:

$$\frac{\partial U / \partial x_n}{\partial U / \partial C} = \frac{\partial P}{\partial x_n} \tag{1}$$

In words, the marginal rate of substitution between the *n-th* characteristic and consumption must be equal to the marginal cost of one extra unit of *n*. Since households consider various combinations of housing components, they form a bid curve for each of the housing components which makes them indifferent. That is, each point along these indifference curves maximizes the utility of households, given the budget constraint and other optimal quantities.

The assumption of competitive markets asserts that producers supply a variation of housing components which enables households to maximize their utility. The variation in housing components is established by the heterogeneity in costs that producers face by supplying the housing components. For instance, suppliers may face different costs dependent on the land size, land typography, and intensity to the exposed (environmental) good. The heterogeneity in the costs functions translates into different offer curves of sellers. The offer curve is the maximum profit each seller can attain given its costs function.

The variation in costs functions of sellers and incomes and preferences of consumers results into an implicit market for an environmental good. To illustrate this, consider Figure A5 which shows a hypothetical *hedonic price schedule* of an environmental amenity. The hedonic price schedule is formed at the points at which the indifference curves of consumers are tangent to the offer curves of suppliers. More specific, households optimize their utility by choosing a level of the environmental amenity (e.g. percentage water around a house) at the point at which their indifferent curve touches the marginal costs of one extra unit of the environmental amenity. To illustrate this, Figure A5 assumes there are four types of consumers and sellers in Figure A5. Consumer 1 does mildly like the environmental amenity and sorts itself to a point with a low intensity. In contrast, consumer 4 likes the environmental amenity to a much greater extent and sorts itself to a point with a higher intensity.

In our study, we are interested in the gradient of the hedonic price schedule with respect to each of the environmental (dis)amenities. For consumers, the amenity gradient can be interpreted as the equilibrium premium that consumers are willing to pay for a higher intensity of green (water) scenery around their house. A similar reasoning applies for environmental disamenities such as air and noise pollution. The environmental disamenities gradient can be portrayed as the horizontal mirror image of Figure A5. In that case, the interpretation of the gradient is the equilibrium price that compensates consumers for accepting a higher intensity in the environmental (dis)amenity (e.g. the health risks).[26]

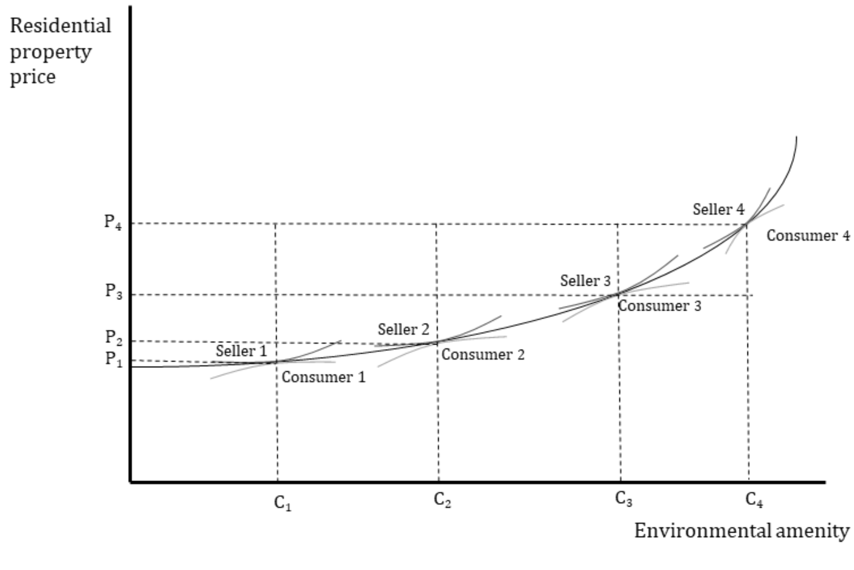

Figure A5: *A hypothetical hedonic price schedule in the residential property market for an environmental amenity*

[26] One overlooked point is that the bid curves of consumers and offer curves of producers for environmental (dis)amenities may be related to the bid and offer curves of housing characteristics. That is, the bid function of consumers for noise pollution may be (partly) determined by the bid function for the number of insulation layers of a house, or the maintenance quality of the building. We consider the importance of the relatedness of bid functions in our empirical section.

A3. Methodological Appendix

Lasso

Although we have a large set of potential control variables, we may not want to include them all in the regression equation due to risks of overfitting. As a solution to prevent overfitting our model, we use a lasso methodology (Tibshirani, 1996). The lasso (least absolute shrinkage and selection operator) selects covariates by only including the covariates whose estimated coefficients are not shrunk to zero. For the sake of argument, suppose that we only employ the lasso for the consumer amenities:

$$\hat{C} = \arg\min_{\beta}\left(\frac{1}{2n}\sum_{i=1}^{n}\left(\log p_{i,n,t} - \alpha EV_i + \beta X_{i,t} + \gamma_n Z_n + \tau_t T_t + \rho P_{i,n} + \delta C_{i,n} + \theta D_{i,n}\right)^2 + \lambda\sum_{j=1}^{k}\omega_j\left|C_j\right|\right) \tag{A1}$$

Where λ denotes the lasso penalty parameter and ω_j is the penalty loading applied to the j-th consumer amenity. Both are referred to as the 'tuning parameters'. The idea behind the lasso penalty parameter is that as λ increases, the estimated coefficients of the control variables are "shrunk" toward zero. Different methods are available to choose the optimal value of λ.

Since the lasso-estimator postulated in (A1) is not suited for inference, we use the double-selection in combination with cross-validation. The double-selection lasso estimator performs the lasso twice. In the first step, it performs a lasso for each of the environmental variables on the control variables (the vectors X, P, C, and D). In the second step, it performs a lasso of the residential property values on the control variables (X, P, C, and D). Both the first and second step generate a list of control variables selected by the lasso. In the third step, a union is generated of the selected variables in steps 1 and 2. The union of selected control variables is then used in the fourth step as input for a regression of the residential property prices on both the environmental variables and the union of selected variables (Belloni et al., 2014). We use cross-validation to select the optimal value of λ for each environmental variable.