The impact of noise on green open space value

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Research article

The impact of noise on green open space value☆

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ABSTRACT

I investigate the effect of noise on the amenity value of urban green open spaces in Prague, Czech Republic. First, I use standard hedonic pricing model exploiting cross-sectional and quasi-experimental variation in the apartment price data and then I analyse green open spaces quality inferred from a quantitative spatial model. Results show that increasing size of quiet green open spaces (with noise below 60 dB) by 10% increases local apartment prices by 0.05% and perceived quality of green open spaces by 1.2%. In a counterfactual scenario, if noise in green open spaces decreases by 2 dB, a noise reduction achieved by implementing 30 km/h speed limit in a city, value of apartments would increase by 0.2% due to increased size of accessible quiet green open spaces.

1. Introduction

Provision of public green open spaces is traditionally very important in urban planning, and empirical evidence shows that people indeed do value green open spaces as they are willing to pay to reside closer to them and in places with higher share of green coverage (Brander and Koetse, 2011; Panduro et al., 2018; Melichar and Kaprová, 2013; Czembrowski and Kronenberg, 2016).

Many studies have focused on the value of urban green open spaces with respect to their size, type and their proximity, but limited number of them have analysed perceived value of open green areas with respect to other factors affecting their attractiveness to local residents.[1] Lack of evidence of which characteristics particularly contribute to perceived value of urban green spaces makes urban planning and green spaces' management difficult when the aim is to deliver maximum value for money. In this paper attention is paid to the effect of noise on value of urban green open spaces. While there is some, although limited and mostly qualitative, evidence of negative effect of noise on green open spaces perceived by users, these negative effects are largely neglected by professionals taking care of green spaces (Ugolini et al., 2022). At the same time, noise is ubiquitous and substantially vary within and between cities. Both the provision of green spaces and low noise at place of residence are well documented public goods that households are willing to pay for, but joint provision of low levels of noise within recreation areas has attracted less attention.

Although there is literature looking at the problem of noise in urban parks (Ugolini et al., 2022; Merchan et al., 2014; Carles et al., 1999), there does not seem to be any study which uses a revealed preferences approach to infer magnitude of the negative effect of noise on the value of open green space. However conceptually similar is Morawetz et al. (2024) who estimate effects of noise in walkable public spaces within 500 metres from a property.

However, there is limited body of literature using revealed preferences methods to analyse interactions of green open spaces' characteristics. Research has so far focused on interactions with crime or local urban characteristics such as density. Albouy et al. (2020) use cross-sectional and panel data to infer the effect of local crime on park values. They analyse Chicago, New York and Philadelphia over the period from 2001 to 2016. They show that omitting the effect of crime underestimates the value of parks. They estimate that parks increase the value of homes in safe neighbourhoods by 2.5% to 2.7%,

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[1] For more details please see Further context section in Online appendix.

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but the value of parks completely vanishes if homicide levels exceed 2.7 annually. Troy and Grove (2008) analysed relationship between the value of parks and crime rates in Baltimore and similarly concluded that high crime rates lower the value of urban parks. While in low-crime areas proximity to parks increases property prices, in high-crime areas proximity to parks decreases their values. Anderson and West (2006) analysed relationship between proximity to parks and crime rates in Minneapolis, and their results are surprisingly different from the two papers mentioned above. Their positive effect of proximity to most open spaces declines faster when crime rates are higher, but their results for most open space types are insignificant. Apart from interaction with crime, they also analysed interactions with density, distance to the CBD and share of population below 18. In the case of neighbourhood parks, they obtained the expected results that the value of parks decreases with distance from the CBD and increases with population density and with share of population below the age of 18.

In this paper, I adopt two distinct revealed preferences approaches to study how noise in green open spaces affects their perceived value. The first approach is rather standard hedonic price model. I explicitly address several features of open green spaces. Beyond their size and proximity, I focus most of my attention on the noise in green spaces and additionally I consider the spatial concentration of open green spaces — whether the accessible green spaces form a few large areas or comprise many smaller separate elements. The analysis is primarily based on cross-sectional apartment transaction data and detailed land use maps are used to measure open green spaces provision. To measure noise, a modelled noise map covering the whole city is used. The main cross-sectional estimation is supplemented with a quasi-experimental approach using opening of an urban underground by-pass which is a part of the city inner ring road diverting a significant share of the road traffic into a 5.5 kilometres long tunnel. On the ground, this has changed traffic flows within the transport network and as a consequence affected noise along the original on-the-ground thoroughfares.

The second approach is conceptually related to the travel cost method (Smith and Kaoru, 1990) which infers recreation value from costs incurred to reach recreation sites. This method has been largely applied to study supralocal recreation areas, such as national parks which are not within everyday reach.[2] While I do not directly observe trips from homes to recreation spaces, I use quantitative spatial model which I infer green open spaces' overall recreational quality based on spatial distribution of homes and frequency of visits in individual green spaces. To proxy where people go for outdoor recreation I use dataset collected in a public participatory GIS (PPGIS) project by Pánek et al. (2021). I then test association between inferred green open space's quality and their noisiness.

My approach is conceptually similar to Czembrowski et al. (2016) who also apply hedonic pricing method and analyse data from public participation GIS survey. However, they directly ask survey participants about perceived quality of green open spaces that could be considered as a stated preferences method. Instead, I only analyse information where residents go to spend free time and using a theoretical model I infer what the quality of recreation places have to be to rationalize number of their visits. This methodology then falls within revealed preferences methods.

The two methods are complementary. The second one similar to travel cost method informs more directly about households' decision-making where to go for outdoor recreation when their home location is fixed. For this setting, it is sufficient if households know qualities of accessible green open spaces and costs (or time) to reach them. Then based on revealed information – where they go for outside recreation – using the quantitative spatial model unobserved quality of these green open spaces is inferred.

Hedonic price model relies on more restrictive assumption. There has to be perfect information about qualities and accessibility of green open spaces for all properties households are willing to bid for. As Whitehead et al. (2008) notes, advantage of revealed preferences methods such as hedonic models is analysis of actual behaviour of individuals who consider costs and benefits they face. However, this condition might not be fully met in this setting. It is possible recreation quality of accessible green open spaces including their noisiness is of lesser importance when compared to other features of prospective properties, and at the same time information about recreation quality is harder to obtain. As a result, quality of green open spaces might not get fully capitalized into property values and the first approach based on travel cost method might provide more conclusive results.

The results show that complementarity of green open space size and low noise is indeed important. The baseline result from the cross-sectional hedonic model reveals that increasing size of quiet green open spaces, those with noise level below 60 dB, by 10% within 600 metres from an apartment increases its value by 0.05%. Similar results, although of slightly higher magnitude, were also found in an alternative research design exploiting variation of noise over time in the aftermath of transport infrastructure improvements.

To further support results from the hedonic analysis, I use quantitative spatial model to infer unobserved green open spaces' quality calibrating the model on data of actual green open spaces' visits. Then in the second step I estimate that additional 10% of quiet green open spaces increase their perceived quality by 1.2%.

The main contribution of this paper is the evidence of negative effect of noise on green open spaces' recreation value. This shows there is not only the direct cost of noise at the property location, but also indirect cost of noise through the channel of reduced recreational value of green open spaces accessible from home. Additionally, this paper presents method of using a quantitative spatial model to infer notoriously hard-to-measure quality of green open spaces from data with number of visitors in green spaces. The results also contribute to the literature on the complementarity of public goods, specifically complementarity of green open space provision and low noise levels. The paper additionally provides some new insights into the indirect negative effects of transport on residential real estate via the indirect channel of decreased recreation areas' value, as transport is the main source of urban noise.

In the following parts, I present data description and construction of variables followed by conceptualization of the multidimensionality of the green open spaces. Then the empirical analysis using hedonic pricing methods is presented followed by theoretical model of green open spaces quality and its analysis. Finally, policy reducing speed limit is evaluated and discussion of the results concludes the paper.

2. Data description and processing

Data used in this project can be generally divided into three groups: spatial GIS vector data with high geographical detail provided by the city of Prague, apartment transaction prices provided by Deloitte and Dataligence, and supplementary socio-demographic data from the 2011 Census. To analyse effect of noise on green open spaces, the key three datasets are noise maps, land use and apartment transaction prices.[3]

[2] As Hanauer and Reid (2017) mention, travel cost method has not been used widely for within-city analysis of recreational space due to insufficient geographical detail of origins-destinations which introduce large measurement error relative to distance between residences and recreational spaces.

[3] All these data sources correspond to time period between 2014 and 2019 as it is detailed below for each dataset separately. The baseline empirical analysis exploiting cross-sectional variation in data implicitly does not assume any change in land use and noise over time (Unlike changes in property prices which are captured by month-specific intercept). However, land use is highly persistent over time and changes within 3 years do not seem to

Spatial data

For the purpose of tractability the whole area of the city of Prague is subdivided into a 100 by 100 metre square grid (the size of a grid cell approximately matches one city block) with a total number of 50,587 grid cells. All the spatial data were then aggregated to these cells to make spatial analysis more efficient.

The main spatial data are obtained from the Prague Geoportal.[4] Detailed land-use vector dataset as of 2017 was used to measure size of 18 categories of green open spaces which are aggregated into the grid. Besides size, each green open space geometry feature has information about its public accessibility which was also used so the green areas are aggregated into publicly accessible green open spaces, or private ones. The data were obtained in June 2017, therefore approximately in the first third of the period of recorded real-estate transactions used in the cross-sectional analysis.

All permeable green areas including agricultural land are shown on the map A.4 in Online appendix. It shows major share of Prague surface is actually undeveloped and the extent of open spaces provision is relatively high by European standards: The size of urban greenery per capita reaches 40 square metres in Prague, while Wien, Munich and Berlin have slightly above 20 square metres and Copenhagen and Budapest are slightly below 20 square metres per capita (IPR Praha, 2017).

However, not all permeable green areas were included in the analysis as some of these spaces are either not publicly accessible, or they are not expected to have any recreational amenity value at all. Green areas within airports and similar facilities serve as a good example. For that reason only the following eight types of open green spaces as defined in the land use map are included: parks, parks-like-sites, woods, park-woods, natural recreation areas, cemeteries, meadows and orchards. These types of land uses are typically associated with higher property prices, but most of the results are not statistically significantly different from zero. Results are reported in auxiliary model in Table A.14 in Online appendix. Land use of sport sites and golf courses are not included as they are expected to provide different kind of amenity value.

One of variables of the primary interest is the size of green open space. The initial assumption is the perceived value of green open spaces is dependent on their size, accessibility, distribution and noise.[5] The accessibility is measured on a walkway network to reflect imperfect connectivity and existing obstacles to walking.

Open green spaces are divided into two categories — large and small ones. Large green open spaces consist of at least two rook-contiguous grid cells (they share a common edge) with at least 50% of green open space coverage in each grid cell. For large green open spaces, proximity is measured as the shortest way on a walkway network from a residential grid cell to the nearest access point of a large green area which is where walking network intersects boundary of green open space. Example of large green open space accessibility is shown on a map A.3 in Online appendix.

Small green spaces are not spanning across multiple grid cells and each grid cell not integrated into a large green open space is simply assigned a size of its green open space. To measure proximity to these small green open spaces, network distance between centroids of grid cells is taken.

Datasets essential for the analysis are noise maps. The dataset is a model for the whole area of the city provided as a vector polygon layer where each polygon represents an estimated equivalent daytime noise level in discrete steps by 5 dB. The noise dataset is constructed for years 2014 and 2016. The analysis is to some extent limited by the fact that for the later noise map the lowest defined noise level is 50 dB, so to make both data sources consistent, noise levels lower than 50 dB in the 2014 dataset are treated as equal to 50 dB. Although not being optimal, this noise level could be still considered as being below urban background noise that is 55 dB according to Day et al. (2007) and the same value is mentioned by Nelson (2008) when reviewing existing literature.

Additional data include demographic characteristics on the level of Elementary statistical units (there are approximately 900 of them in Prague), public transit stations and stops, location of retail shops, public amenities such as public toilets and scenic vistas, gross floor areas of buildings and estimated number of residents and jobs in each grid cell. More information about these supplementary spatial datasets are provided in Online appendix.

Real estate transaction prices

Two separate real estate transaction datasets are used, one for the cross-sectional analysis and the second for the quasi-experiment. Both datasets are provided by Deloitte Real Estate Advisory Czech Republic and Dataligence and contain all transactions of apartments in Prague registered by the Cadastral office which administers all real estate ownership transfers in the Czech Republic. The two datasets are very similar and the only difference is in time coverage and specific information about buyers. The time period of the first dataset for the cross-sectional analysis is from July 2016 to December 2019 and it contains in total approximately 60,000 observations. While observations for later years would be also available, the covid pandemic might violate the assumption of a single housing market over time and therefore are not used in the analysis. The second dataset starts in 2014 and ends in December 2017. Six months period after the opening of the tunnel is dropped from the data as an adjustment period. That leaves one year and nine months of data before and after the treatment. Both datasets are cleaned to contain only standard market transactions, excluding special cases such as subsidized sales of publicly owned apartments, property transfers within a family, ordered auctions and other non-standard transactions.

Each transaction is exactly localized with GPS coordinates, a day of processing at the cadastral office, size of an apartment, the real estate category (new development, buildings with brick load bearing

be quantitatively important. On the other hand, noise has changed over the time period studied: for the locations in the apartment sample it on average decreased by −0.45 dB between 2014 and 2016 with standard deviation of 2.53 dB. Cross-sectional analysis uses apartment transaction prices from 2016 to 2019, so any change in noise since 2016 introduces measurement error into the independent variable, attenuating results towards zero (Greene, 1990). Therefore results from the cross-sectional analysis could be interpreted as lower-bound estimates.

[4] https://geoportalpraha.cz

[5] Combinations of size and accessibility are common in existing literature. For instance Panduro et al. (2018) jointly estimate effect of parks' proximity and their area within a radius of 1000 metres. Albouy et al. (2020) estimate effect of proximity to parks in 100 metres-wide buffers, up to 200 or 600 metres away from a park, depending on specification. Anderson and West (2006) focus on effect of log of distance to green open spaces, which they additionally interact with green open spaces' size. Melichar and Kaprová (2013) similarly study interaction of size and proximity, but conversely use log of area and distance in levels, and additionally they estimate effect of share of green spaces in a neighbourhood. Brander and Koetse (2011) analyse in their meta-analysis effects of proximity only. Although not common, there are articles which consider green open spaces' spatial concentration, such as Cho et al. (2008) who measure number and mean size of forest patches and their perimeter to area ratio, or for instance Zhang et al. (2020) who analyse effect of green open spaces on walking and include variable of park's shape as a relationship between its size and size with additional buffer. To my knowledge noise has not been included in hedonic valuation of green spaces, but Morawetz et al. (2024) analysed effect of noise on walkable public space within 100 and 500 metres from a property, and for noise exceeding thresholds from 45 dB to 65 dB.

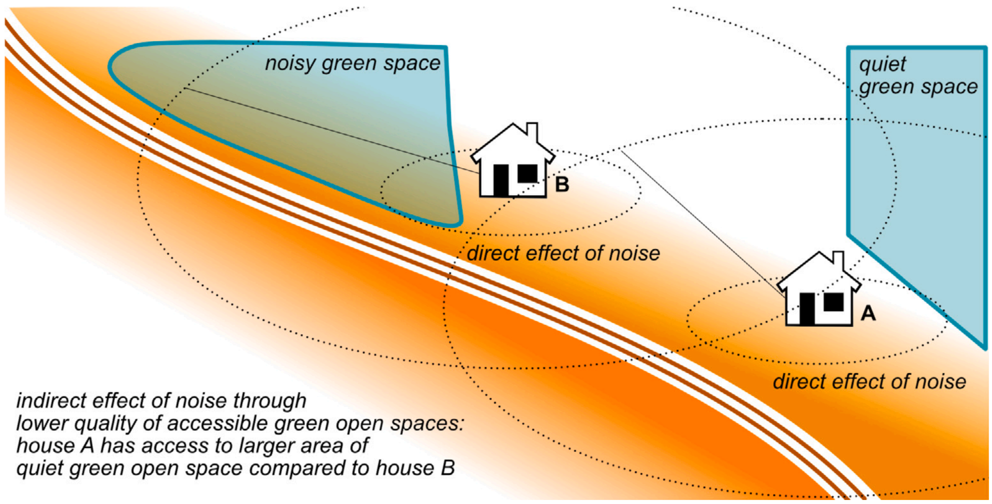

Fig. 1. Direct and indirect effects of noise.

structure, historic buildings and prefabricated buildings from 1960's to 1990's) and the sale category (first sale from a developer, resale between owners).

Additional information about buyers are available in the cross-sectional data: whether buyer is a company, individual or more individuals. If buyer is an individual or more individuals, an age category in 5-years bins is provided for each of them. For each person there is an indicator whether is a Czech or former Czechoslovak citizen. Finally, there is an indicator if the property is bought jointly by a married couple.

3. Empirical analysis

The empirical analysis is divided into three parts. The first and second parts are hedonic price models which infer implicit prices of green open spaces contingent on their mean noise levels. However, each part relies on a different identification strategy. The first one investigates a cross-sectional variation in green open spaces and their characteristics. The second explores variation in noise caused by a quasi-natural experiment of opening a new road tunnel by-pass. The second strategy is described in more detail in the respective part.

Both hedonic approaches use individually recorded apartment transactions as observations. Each observation is exactly localized and contains set of apartment, building, time and location-specific characteristics, while cross-sectional data also contain some information about buyers. The dependent variable is log of apartment transaction price and as explanatory variables of interest size of green open spaces by noise levels is used, as well as other features assumed to have effect on green open space amenity value (see Fig. 1).

The third approach differs substantially from the two previous hedonic models. Instead of relying on assumption of green open spaces amenity value being capitalized into property values, theoretical model linking parks' accessibility, quality and likelihood of being visited is brought to real data which record where people spend their free time. The model is quantified and otherwise unobserved park quality is inferred from the model in the first stage. Then in the second stage green open space quality is regressed on observable features of interest.

Regarding definition of green open spaces' noisiness, throughout the main body of the paper green open spaces are grouped into discrete categories by their noise level. Based on initial models, preferred specifications include only two categories with 'quiet' green open spaces for which noise level does not exceed 60 dB, and 'noisy' green open spaces for which noise exceeds 60 dB threshold. While this threshold was data-driven for this particular analysis[6] , there are other studies which place 'noisiness' threshold in this region. For instance Paunović et al. (2009) analyse noise in streets and they classify them as noisy if they exceed 65 dB, or quiet if their noise level is below 55 dB. Gidlöf-Gunnarsson and Öhrström (2010) investigate the effect of quiet courtyards accessibility and they split the sample by street noise with a threshold value at 62 dB. Then the US Environmental and Planning Agency set in 1974 the limit of 55 dB "on acceptable sound volume in order to prevent 'activity interference' and 'annoyance'" (Moudon, 2009, p. 168). Finally, a meta-analysis based on European and Japanese cities conducted by Babisch (2008) concluded there is no increased risk of myocardial infarction for exposures to road traffic noise below 60 dB. However, the risk increases for higher noise. Setting the 'noisiness' thresholds at 60 dB seems therefore to be within the range of values already used before.[7]

[6] Alternative models with green areas divided into 5 dB groups were estimated, with mostly positive effects for noise below 60 dB (Although the estimates for group below 55 dB are both economically and statistically insignificant) and mostly negative effects for groups above 60 dB (The only group with persistently positive coefficient are green spaces with noise between 65 dB and 70 dB, which are only statistically significant at 10% level when controlling for spatial concentration of green spaces). Additionally, alternative thresholds between the quiet and noisy green spaces were tested. When moving the threshold down gradually down to 55 dB, positive effects of green spaces decrease in magnitude and turn insignificant, likely due to the major role of green spaces in 55 dB to 60 dB group and lower overall provision of quiet green spaces. On the other hand, moving the threshold up towards 65 dB if anything rather increases the effect of quiet green open spaces, while coefficient for noisy green spaces is more volatile and rather positive, but never significant on conventional levels. Finally, at the threshold of 60 dB size of accessible quiet and noisy green spaces is about the same for an average apartment in the data. See Tables A.2, A.3 and A.4 in Online appendix for more detail.

[7] An alternative approach is shown in Online appendix where the mean noise level for all accessible green spaces is used. Qualitatively, the results are similar, but the effect of noise in green open spaces in the baseline cross-sectional specification is found only for locations where accessible green spaces are spatially concentrated. As interaction with green spaces' spatial distribution complicates interpretation, simpler models in the main body of the paper are preferred.

Cross-sectional hedonic model

Full hedonic model including individual measurable characteristics of green open spaces is estimated first. The model considers open green spaces accessible within 600 metres from a residence via walkway network. Green open spaces are grouped into categories by their noise level. Implicit value of green open spaces' characteristics are estimated according to the following equation:

$$\log P_{iegct} = \gamma_L \log(G_g^{green\leq 60dB}) + \gamma_H \log(G_g^{green>60dB}) + \boldsymbol{X}_i\alpha^I + \boldsymbol{D}_e\alpha^{II} + \boldsymbol{S}_g\alpha^{III} + \eta_c + \varsigma_t + \varepsilon_{iegct} \tag{1}$$

The dependent variable $\log P_{iegct}$ is natural logarithm of price of an apartment i, located in an elementary statistical unit e, grid cell g, cadastral area c and sold in a year and month t.

Variables $G_g^{green<60dB}$ and $G^{green>60dB}$ are natural logarithms of accessible green spaces with mean noise level below (or equal to) and above the 60 dB threshold respectively.

The vector X contains apartment and buyer specific controls including log of apartment size, a property type (new, old), a construction type (brick, prefabricated panels), an age of building, connection to gas and a log of distance to the CBD. Buyer controls include the type of sale (developer to household, household to household), a dummy if buyer's age is known (unknown is for firms buying property), buyer's age and age squared, whether buyers are a married couple and if married whether they are in the age group 25 to 45.

The vector D contains demographic controls from 2011 Census available at the Elementary statistical unit level e and it contains a share of children below the age of 15, a share of residents above the age of 65, a share of college educated residents and a share of unemployed.

The vector S of local area controls on the level of apartments' grid cell g contains equivalent spatial concentration of green spaces, daytime noise, elevation, terrain slope, a dummy for the Southern slopes, a log of jobs within a grid cell, proximity to the metro or a train station, proximity to a tram or a bus stop, gross floor areas within 250 metre radius and a number of retail stores within 250 metre radius.

The last terms are η_c cadastral area fixed-effects, τ_t year and month fixed-effects and ε_{iegct} is a randomly distributed residual.

The baseline models are all estimated according to Eq. (1). The column (3) is the full model containing all terms in the equation while the columns (1) and (2) show results of simpler specifications with some variables omitted.

The column (1) shows the most simple specification with only a set of property-specific and local control variables and logs of public and private (non-publicly accessible)[8] green spaces. Estimates do have expected signs although only size of publicly accessible green open spaces is statistically significant on conventional levels. Increasing size of green open spaces by 10% is associated with increase of apartment prices by 0.17% (see Table 1).[9]

In the column (2) additional control variables capturing local demographics and land use are added which cause the effect of green open space size to drop roughly by one third and with significance decreasing to 10 per cent level. Variable hhi measuring spatial concentration of accessible green open spaces with the Herfindahl–Hirschman concentration index is added here. While its effect is not statistically significant, it is correlated with both noise in green open spaces and size of green open spaces and when added into specification it typically decreases estimated effects of variables of interest.[10]

Table 1
Baseline estimation — effects of open green spaces.

dep. var.: log of property price	(1)	(2)	(3)
log(green_public + 1)	0.0167***	0.0104·	
	(0.0028)	(0.0054)	
log(green_public_noise_50_60 + 1)			0.0049*
			(0.0020)
log(green_public_noise_60plus + 1)			−0.0024
			(0.0054)
hhi		0.0482	0.0569
		(0.0378)	(0.0363)
log(green_private + 1)	0.0011	0.0032·	0.0030·
	(0.0019)	(0.0018)	(0.0018)
noise_D_17	−0.0011	−0.0012	−0.0009
	(0.0007)	(0.0007)	(0.0007)
Apartment controls	✓	✓	✓
Local area controls		✓	✓
Demographic controls		✓	✓
Month and cadaster FE	✓	✓	✓
Num. obs.	60 243	55 512	55 512
R^2 (full model)	0.8341	0.8357	0.8358
R^2 (proj model)	0.7750	0.7759	0.7761

$***p < 0.001$; $**p < 0.01$; $*p < 0.05$; $^{\cdot}p < 0.1$
Explained variable in both models is log of apartments' price. Standard errors clustered at the cadastral area level are reported in parentheses.
Apartment controls include log of apartment size, property type (new, old), construction type (brick, prefabricated panels), building age, connection to gas and log of proximity to the CBD.
Buyer controls include type of sale (developer-household, household-household), dummy if buyer's age is known (unknown is for firms buying property) buyer's age and age squared, whether buyers are married and whether married and in age group 25 to 45.
Local area controls contain elevation, terrain slope, dummy for south slopes, log of residents plus 1 within a grid cell, log of jobs plus 1 within a grid cell, proximity to a metro or train station, proximity to a tram or bus stop, gross floor areas within 250 metres radius and number of retail stores within 250 metres radius.
Demographic controls from 2011 Census on Elementary statistical unit level contain share of children below the age of 15, share of residents above the age of 65, share of college educated and share of unemployed.

The last model in column (3) estimates separate effects for accessible green open spaces by their noisiness. Whereas increasing area of accessible quiet green open spaces (with noise below 60 dB) by 10% increases value of local properties by 0.05%, increasing area of noisy green open spaces does not affect property values. To compare this finding with existing literature, for instance evaluating results of Panduro et al. (2018), they find an effect of 0.66% when increasing size of parks by 10%. However, as mentioned earlier, their effects could be larger as they study inner city and city parks only. Evaluating estimates of Melichar and Kaprová (2013) done for the city of Prague, increasing provision of parks and urban forests within a cadastral area by 10% increases property values by 0.1%. Almost identical result of 0.09% was found for the city of Lodz by Czembrowski and Kronenberg (2016).

Additionally, possible heterogeneity in effects based on likelihood of having children was tested, but it does not seem households which might have children would be willing to pay more for apartments with higher accessibility of quiet green open spaces. However, there is some evidence the effect is stronger in places with higher share if children, similar to finding by Anderson and West (2006). Results are reported in table A.5 in Online appendix.

[8] These non-publicly accessible green open spaces contain only categories of parks, parks-like-sites, woods, park-woods, natural recreation areas, cemeteries, meadows and orchards.

[9] Alternative log-linear specification (Table A.15 in Online appendix) shows value of an additional hectare of green open spaces is 0.26% when overall provision of green spaces is low, but it declines sharply with overall size of green spaces. The result is somewhat smaller in magnitude when compared to findings by Panduro et al. (2018), who find an additional hectare of parks in Copenhagen to increase property values by 0.33%. However, it seems plausible as they analyse inner city and city parks only.

[10] Additional model comparisons are included in Table A.2 in Online appendix. In particular, effects of more granular categories of green spaces by noise are reported, as well as exclusion of hhi variable.

Time variation in noise

On the 19th September 2015, new underground segment of the Prague inner-city motorway ring was opened. As a consequence of opening the tunnel by-pass, the road network experienced significant changes in the daily automobile traffic volumes. While the area above the new tunnel mostly experienced decrease of on-ground traffic, previously unconnected segments of the inner-ring such as some radial arterial roads and some areas in the city centre experienced increase of automobile traffic. The event is assumed to be an exogenous shock to the noise in open green areas which is largely caused by car traffic.

This identification strategy exploiting change in noise mitigates some of the endogeneity concerns related to the cross-sectional variation in the data, especially omitted variable bias when some unobserved feature is correlated with noise in green open spaces. As this method employs very granular fixed effects, either at road segment or grid-cell level, all features which do not change over time will be captured by locally-specific intercept. Examples of these include for instance accessibility, specific local ecosystem services or biodiversity, and quality as long as quality was not affected by the construction activity related to the underground by-pass construction. However, this approach is unable to disentangle between possible negative effects all caused by automobile traffic, for instance to what extent the negative effect is driven by noise, or local air pollution.[11]

Models exploiting quasi-natural experiment of noise variation over time are estimated according to estimation equation similar to Eq. (1):

$$\log P_{iegmct} = \gamma_L \Delta \log (G_g^{green \le 60dB}) \mathbb{1}(t > t^*) + \boldsymbol{X}_i \alpha^I + \boldsymbol{D}_e \alpha^{II} + \boldsymbol{S}_g \alpha^{III} + \rho_m + \eta_c + \varsigma_t + \varepsilon_{iegmct} \tag{2}$$

The explanatory variables used are the same as in Eq. (1). The only difference is estimation of the effect of change in logs of accessible green open space areas between 2016 and 2014, which is denoted by $\Delta \log (G_g^{green<60dB})$. As noise levels changed, size of green open spaces with noise below 60 dB has also changed and positive values indicate (log) increase of accessible green open spaces. Indicator variable $\mathbb{1}(t > t^*)$ is equal to one for an apartment transactions done in time t after the opening of the tunnel by-pass on the 19 September 2015 plus six month of adjustment period[12] (time t^*), and zero for dates before 19 September 2015. Control variables do not differ from Eq. (1) except of noise within the grid cell where apartment is located which is again used as a change and in interaction with $\mathbb{1}(t > t^*)$ variable to take into account the direct effect of noise change in a grid cell g. ρ_m is additional cadastre-year fixed effect which allows for heterogeneity in apartment price trends across different cadastral areas.

The first two columns of Table 2 are estimated for the whole sample. Both columns (1) and (2) show the effect of increased size of quiet green open spaces has expected sign and twice the magnitude of the cross-sectional results, but only result in column (1) is significant at the 10% level.

Insignificant results with smaller magnitude could be driven by measurement error in the noise variable which would bias estimates towards zero. The measurement error could result from the design itself. It is assumed the change in noise between 2014 and 2015 is completely driven by traffic adjustment after the tunnel opening in September 2015. For that reason transactions completed before this date assume noise levels as of 2014, and transactions after the threshold date plus adjustment period assume noise levels as of 2016. In reality it is possible other major changes in noise elsewhere in the city could occur anytime between 2014 and 2016 so this particular 'before-after' thresholds might not be accurate for the whole city and likely introduces measurement error.

Table 2
Models exploiting change of noise.

	Whole sample		Affected location	
dep. var.: log of property price	(1)	(2)	(3)	(4)
log(green_public_noise_50_60_change)	0.009·	0.011	0.028*	0.041*
	(0.005)	(0.009)	(0.014)	(0.017)
hhi	0.088·		0.216	
	(0.048)		(0.136)	
log(green_private + 1)	0.001		0.008*	
	(0.002)		(0.004)	
noise_D_ch_X_after_intervention	0.006*	0.002	0.003	0.003
	(0.003)	(0.004)	(0.007)	(0.023)
Apartment controls	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
Cadaster-year FE	✓	✓	✓	✓
Local area controls	✓		✓	
Demographic controls	✓		✓	
Road segment FE	✓		✓	
Grid cell FE		✓		✓
Num. obs.	47 215	49 272	6394	6574
R^2 (full model)	0.586	0.666	0.489	0.558
R^2 (proj model)	0.436	0.393	0.349	0.270

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$
Explained variable is log of apartment price. Standard errors clustered at either road segment (columns 1 and 3), or grid cell (columns 2 and 4) level are reported in parentheses.
Apartment controls include log of apartment size, property type (new, old), construction type (brick, prefabricated panels), building age, connection to gas and log of proximity to the CBD.
Local area controls contain elevation, terrain slope, dummy for south slopes, log of residents plus 1 within a grid cell, log of jobs plus 1 within a grid cell, proximity to a metro or train station, proximity to a tram or bus stop, gross floor areas within 250 metres radius and number of retail stores within 250 metres radius.
Demographic controls from 2011 Census on Elementary statistical unit level contain share of children below the age of 15, share of residents above the age of 65, share of college educated and share of unemployed.

To tackle this issue, the models in columns (1) and (2) are re-estimated using only observations from cadasters most affected by the new infrastructure opening. According to models (3) and (4), increasing size of quiet green open spaces by 10% increases value of apartments by 0.3% and 0.4% respectively, some six to eight times larger effect than one found in cross-sectional analysis.

Higher magnitudes of effects could be caused by data-smoothing in the noise maps, a problem discussed in Online appendix. As a result, it might be possible that the true change in noise is not fully captured in the noise maps and the change is attenuated. If this is the case, regressing housing prices on these downward-biased change in noise would result into upward-biased estimates.

Analysis shown in Online appendix has shown that on-site measured noise change is approximately 2.5 times higher in magnitudes compared to the change calculated from the noise maps. This is suggestive evidence that the noise maps indeed do not fully capture the true change in noise levels. If the 2.5 multiple holds in general, the overall estimates from columns (1) to (4) would drop to some −0.4% (column 1) to −1.6% (column 4), which is more aligned with the results from the cross-sectional baseline estimates.

Additionally, higher magnitude of estimated effect for the subset of observations directly affected by the tunnel bypass could be caused either by the heterogeneity of the effect in these areas, or by unobserved improvements to the green open spaces that took place during the construction of the tunnel itself. The second reason could be possible as majority of green spaces directly affected by the construction works were indeed refurbished at the end of the project. However, the share

[11] This problem is notorious to studies investigating either effects of road noise, or effects of traffic-caused air pollution. Héritier et al. (2019) try to disentangle between the two when analysing effects on myocardial infarction mortality. They find the effects of noise do not change when controlling for air pollution, but conversely effects of air pollution are lower when controlling for noise. This might be a weak evidence, at least from the health perspective, that noise has an effect independent of air pollution.

[12] All observations falling into the adjustment period are excluded.

of accessible green open spaces directly affected by the construction is relatively small.

Despite some variation in magnitudes of estimated coefficients of interest, the models follow the same pattern and it might be concluded the analysis exploiting variation in noise before and after the major transport network adjustment is aligned with the results obtained from the baseline cross-sectional analysis.

Quality inferred from quantitative spatial model

In the third empirical section I approach the problem differently. Instead of estimating effects of open green space characteristics on apartment prices, I use a quantitative spatial model which I calibrate with observed data of green open spaces visits to back out green open spaces' overall quality which rationalizes such behaviour. Collapsing all qualities of green open spaces into one variable is appealing, because one does not have to make any assumptions about what residents actually value more or less about green open spaces. In fact, as Ugolini et al. (2022) noted, even professionals in open green spaces do not seem to be aware of what residents actually value about green spaces. Then in the second step I regress inferred open green spaces' qualities on set of variables which are assumed to affect their recreational value including size of quiet and noisy green open spaces which are of the primary interest.

Quality of open green spaces as a single variable. To construct a continuous variable capturing the perceived quality of open green spaces, I use a quantitative spatial model framework based on Ahlfeldt et al. (2015). This class of models allows, among other things, to infer the unobserved 'attraction force' (quality, in this case, and wages in the original model) if the number of incomers and number of people by their place of residence are observed. I use this framework and, instead of inferring wages from commuting patterns, I infer quality of green open spaces from observed workers' places of residence and choice of green open spaces where they spend their free time, given network distances from residences to all accessible green open spaces. This quality variable is labelled $quality\_model$.

In this case the quantitative spatial model uses data from a participatory GIS project which attempted to collect Prague residents' sentiment about different places in the city (Pánek et al., 2021).[13] Using public participation GIS to collect data and evaluate qualities of green open spaces is not new. For instance Ives et al. (2017) conducted such a survey to map qualities of green spaces in a suburb in New South Wales. However, these studies usually limit analysis to descriptive statistics, heatmaps, or statistical association between respondents' opinions and green spaces' characteristics. If these methods would be used to infer information about preferences, it would fall into a category of stated preferences methods. Instead, using the quantitative spatial model framework, I use only information where in green open spaces residents spend time, as they recorded this information in the participatory GIS project. I use this data entry to infer what quality individual green open spaces must have to rationalize number of their visits given their proximity to residential locations. Due to this construction the method falls within revealed preferences methods which seems to be rather rare in analysing participatory GIS data.

The city is assumed to be monocentric with all workers earning wage w, paying commuting costs c_i to reach their workplace from their place of residence, where they pay rent r_i. Parameter $1-\beta$ is expenditure share on housing. The simplifying assumption is that each worker chooses one green open space j (later referred to as a park) out of all the accessible parks J that he or she visits for recreation. Following Ahlfeldt et al. (2015) and Monte et al. (2018), the indirect utility of a worker o is given by size of park S_j, with μ which is parks' value elasticity with respect to their size, and decreases with the time costs of walking to the park d_{ij} from a residence. Each worker has an idiosyncratic taste shock for amenities provided by a pairing of residence and park to go to for recreation z_{ijo}. Distribution of the taste shock follows Fréchet distribution with $F(z_{ijo}) = e^{-B_i Q_j^{-\epsilon}}$ where B_i is a mean amenity value of place of residence, and Q_j is a mean amenity value of a park j. $\epsilon > 1$ controls the dispersion of individual taste shocks. The larger is ϵ, the more homogeneous tastes are among residents.

$$V_{ijo} = \frac{z_{ijo} S_j^{\mu} w}{d_{ij} c_i r_i^{1-\beta}} \tag{3}$$

Following Ahlfeldt et al. (2015) and Monte et al. (2018), a discrete choice model of choosing a place of residence and a park with assumed distribution of idiosyncratic taste shock could be solved, so there is a probability π_{ij} of living in i and going to park j. As wages are constant for all residents, they drop out of the equation. The probability of living in i and choosing park j for recreation depends on the amenity value and rents in i, size and quality of park j, and the distance d_{ij} between them, which are all in the numerator (also called bi-lateral resistance) relative to all other options in the economy (multi-lateral resistance) in the denominator — which is the sum of the same term for all combinations of residences u and all parks v.

$$\pi_{ij} = \frac{B_i Q_j (S_j^{\mu}/d_{ij} c_i r_i^{1-\beta})^{\epsilon}}{\sum_{u=1}^{U}\sum_{v=1}^{V} B_u Q_v (S_v^{\mu}/d_{uv} c_u r_u^{1-\beta})^{\epsilon}} \tag{4}$$

Further, probability $\pi_{ij|i}$ of choosing park j conditional on living in place i simplifies the term as residence-specific terms in the numerator and denominator will cancel out:

$$\pi_{ij|i} = \frac{Q_j (S_j^{\mu}/d_{ij})^{\epsilon}}{\sum_{v=1}^{V} Q_v (S_v^{\mu}/d_{iv})^{\epsilon}} \tag{5}$$

The probability of choosing park j conditional on living in i can immediately be used to relate the number of park visitors N_j and number of residents N_i living in locations I, because the probabilities of choosing park j conditional on living in i multiplied by population in i sums up to the overall number of visitors of a park j: $N_j = \sum_{i=1}^{I} \pi_{ij|i} N_i$. Substituting in Eq. (5) yields:

$$N_j = \sum_{i=1}^{I} \frac{Q_j (S_j^{\mu}/d_{ij})^{\epsilon}}{\sum_{v=1}^{V} Q_v (S_v^{\mu}/d_{iv})^{\epsilon}} N_i \tag{6}$$

This expression in Eq. (6) states that the number of visitors N_j of a park j is a sum of probabilities $\pi_{ij|i}$ of recreating in a park j conditional on living in i multiplied by respective populations N_i of locations i. The fraction of population visiting a park j and living in i is given by the quality of a park Q_j and its size S_j to the power of μ, which captures the elasticity of value with respect to the park's size, divided by the cost d_{ij} of reaching j from i. The whole term is raised to the power of ϵ, a parameter that governs the dispersion of individual idiosyncratic preferences for combinations of places to live and places for outdoor recreation, which are assumed to be randomly drawn from the Fréchet distribution. The denominator is a summation of the same structure of all other accessible parks v, with their qualities Q_v, sizes S_v and proximities d_{iv} from i to v raised to the power of ϵ. Number of residents N_j, number of park visitors N_j, park sizes S_j and distances d_{ij} are measured and parameter μ is estimated in a separate model. The only unobserved variable in Eq. (6) is a vector of open space quality $\mathbf{Q}$ with a length of J, number of parks. Ahlfeldt et al. (2015) show that there is a unique vector that solves the system of J Eqs. (6); as long as one element of $\mathbf{Q}$ is normalized to one, the relative quality of parks is inferred.

[13] The data are in particular under-representing residents older than 60 years (23% in population and only 7% in the PPGIS data). If tastes for green open spaces' quality and costs of their accessing differ between younger and older residents, then inferred park qualities rather reflect tastes of the younger cohorts. For more details regarding the Public participation GIS data see Online appendix.

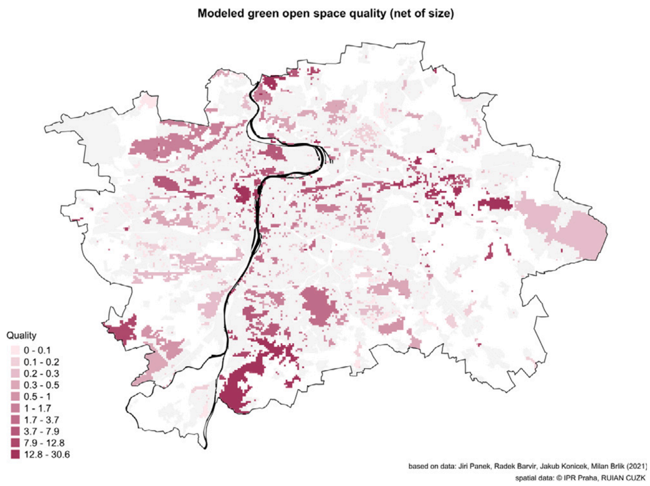

Fig. 2. Quality of accessible green open spaces.

The vector of park quality **Q** is solved numerically when the model is brought to the data (see Fig. 2). The number of users of open green spaces N_j is proxied with data collected by Pánek et al. (2021), who in their public participation GIS project asked multiple questions regarding quality of life – for instance, which places are neglected, or which do not feel safe – and let participants select places on a map. I use particular entries labelled "This is where I spend my free time". Out of 15,989 entries in this category, 8086 were geo-located within accessible green open spaces with recreation potential, as defined in this project. This shows that open green spaces are indeed important places for recreation. To be consistent with the theoretical model, and assuming each resident picks one open green space for recreation, the number of visitors in each open space is scaled up so that the sum of visitors matches the Prague population reported in the 2011 census.

Residential locations i consist of square grid cells with an area of one hectare for which population N_j is aggregated from the 2011 Census data reported at the building level. Lastly, the cost of reaching an open space j from a residence location i is given by $\tilde{d_{ij}}^{\tau}$, where $\tilde{d_{ij}}$ is the network distance between residence i and open green space j.[14] τ is the elasticity of probability of visiting a green open space with respect to its proximity, and it is currently set to 5, following Heblich et al. (2020), who used the same functional form, but measured that elasticity in the case of commuting to work. ε measuring the dispersion of individual tastes for home locations and open spaces is set to the value of 5, similar to other literature (Ahlfeldt et al., 2015; Heblich et al., 2020) which models commuting to jobs. This application is, however, less sensitive to the choice of ε, which affects the variance of calculated vector **Q**, but the ordering of individual parks by their inferred quality remains unchanged.

Effect of noise on green open spaces quality. If noise is perceived as nuisance in green open spaces it should, all else equal, translate into lower green open space quality **Q** which was inferred from residents' behaviour. To test this, empirical equation (7) is estimated using OLS model.

$$\log Q_{igc} = \gamma_L \log(G_{ig}^{green \leq 60dB}) + \gamma_H \log(G_{ig}^{green > 60dB}) + \boldsymbol{X}_{ig}\alpha + \eta_c + \varsigma_t + \varepsilon_{igct} \tag{7}$$

Dependent variable $\log Q_{igc}$ is natural logarithm of inferred green open space quality, $G_i^{green<60dB}g$ and $G_i^{green>60dB}g$ are areas of green open spaces with noise levels below and above 60 dB respectively, X_{ig} is a vector of controls, η_c and ς_t are cadastral and month fixed effects respectively (in column 3) and ε_{igct} is a random error term.

Results are reported in Table 3. Models in columns (1) and (2) are estimated with green open spaces as individual observations while in the column (3) observations are apartments for which all variables are constructed as size-weighted means of accessible green open spaces' characteristics.

All three models yield results of expected directions and are significant on conventional levels. Preferred specification in column (2) shows the overall quality of green open space increases by 1.2% when size of quiet green open spaces increases by 10%, whereas increasing size of noisy green open spaces is not associated with higher quality. Consistent with earlier findings, including variable hhi controlling for spatial concentration of green open spaces substantially decreases magnitude of the coefficient of interest.

Model in column (3) which is estimated with apartments as units of observation has the same qualitative results, although the effect of quiet green open spaces is roughly one third smaller in magnitude. This

Table 3
Effect of noise on open space quality.

	Green open spaces		Apartments
dep.var.: log of green open space quality	(1)	(2)	(3)
log(green_public_noise_50_60 + 1)	0.200***	0.116*	0.059*
	(0.053)	(0.056)	(0.029)
log(green_public_noise_60plus + 1)	−0.028	−0.092	−0.047
	(0.068)	(0.068)	(0.054)
gr_retail_n	−55.216**	−48.111**	−0.089
	(17.871)	(17.869)	(0.117)
gr_walkway_n	−0.056***	−0.041*	−0.087
	(0.016)	(0.017)	(0.103)
gr_view_n	0.113**	0.117**	0.143**
	(0.042)	(0.044)	(0.054)
gr_toilets_n	0.049*	0.050*	0.092
	(0.024)	(0.021)	(0.083)
gr_transit_n	−0.143*	−0.114·	−0.210
	(0.069)	(0.068)	(0.187)
hhi		2.160***	1.607**
		(0.379)	(0.515)
log(green_private + 1)	−0.032·	−0.024	−0.002
	(0.017)	(0.016)	(0.022)
noise_D_17			−0.011**
			(0.004)
District FE	✓	✓	
Cadaster FE			✓
Apartment controls			✓
Local area controls			✓
Demographic controls			✓
Num. obs.	1032	1017	51 602
R^2 (full model)	0.718	0.736	0.851
R^2 (proj model)	0.218	0.250	0.424

$***p < 0.001$; $**p < 0.01$; $*p < 0.05$; $^{\cdot}p < 0.1$
Explained variable in both types of models is log of open green spaces' quality inferred from the quantitative spatial model. In columns (1) and (2) heteroscedasticity-robust standard errors are reported in parentheses. In the column (3) standard errors clustered at the cadastral area level are reported in parentheses.
Apartment controls include log of apartment size, property type (new, old), construction type (brick, prefabricated panels), building age, connection to gas and log of proximity to the CBD.
Buyer controls include type of sale (developer-household, household-household), dummy if buyer's age is known (unknown is for firms buying property) buyer's age and age squared, whether buyers are married and whether married and in age group 25 to 45.
Local area controls contain elevation, terrain slope, dummy for south slopes, log of residents plus 1 within a grid cell, log of jobs plus 1 within a grid cell, proximity to a metro or train station, proximity to a tram or bus stop, gross floor areas within 250 metres radius and number of retail stores within 250 metres radius.
Demographic controls from 2011 Census on Elementary statistical unit level contain share of children below the age of 15, share of residents above the age of 65, share of college educated and share of unemployed.

[14] The point of reference for residences i is always the centre of a grid cell. The same holds for small green areas that do not exceed one grid cell. For large open green spaces, the reference point is the nearest entrance into the open green space on a walkway network from i to j.

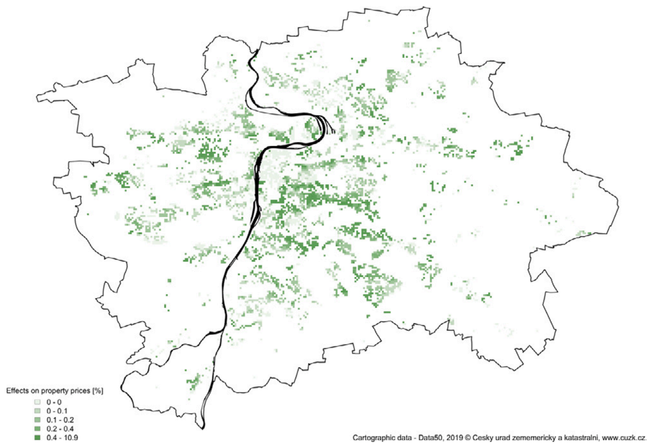

Fig. 3. Effect of 2 dB decrease in green open spaces.

could be driven by different weighing with more observations in areas where effect of silent green open spaces could be weaker.

To briefly comment on effects of other features thought to contribute to green open spaces' amenity value, there is strong evidence of positive effect of green open spaces' concentration and of scenic views. There is some evidence that public toilets increase amenity value. On the other hand, density of walkways, proximity to public transport and to retail is rather negatively associated with quality of green open spaces.

This section has shown evidence of negative association between noise and green open space quality making noisier green open spaces less likely to be chosen for recreation.

4. Policy evaluation

As majority of urban noise is caused by road traffic, the results have implications for transport planning and management.[15] One instance are currently frequently discussed policies of decreasing the speed limit in urban areas from 50 km/h to 30 km/h (30 mph to 20 mph). Based on data from Switzerland, Rossi et al. (2020) assume that such a speed limit reduction would decrease noise level by 3 dB which is consistent with more recent review of lower speed limits implemented in Zurich, Paris, Brussels, Berlin and Graz with average decrease of noise by 2.5 dB (Yannis and Michelaraki, 2024). Older literature review by Desarnaulds et al. (2004) mentions noise reduction in a similar range from 2 to 4 dB.

Being rather conservative, I evaluate my model at 2 dB noise reduction which is on the lower bound reported in the literature taking into account that not all green spaces and properties might be actually affected. However, as green spaces currently unaffected by excessive road traffic-caused noise do likely have noise levels below 60 dB, they are not affected in the counterfactual analysis, as they are always quiet. The evaluation is done on a sample of approximately 60,000 apartments which was used for the cross-sectional analysis. Due to the drop in noise, more quiet green open spaces with noise below 60 dB would be accessible. Green open spaces which are currently exposed to noise ranging from 60 dB to 62 dB would become quiet after the intervention of 2 dB noise reduction. Median increase in accessible quiet green open spaces is 0.77 hectares and mean is 1.1 hectares. Mean log difference is green open space size is 0.40. Decreasing noise in green open spaces by 2 dB actually increases on average provision of silent recreation areas by 50%. Evaluating at the coefficient from the baseline cross sectional analysis (0.0049), decrease of noise in green open spaces by 2 dB would increase apartment values by 0.2%. To compare it, the same noise decrease would increase apartment values also by 0.2% through direct effect assuming the direct cost of noise is 0.1% per dB, which is at lower bounds of what is found in literature (Brander and Koetse, 2011 report their estimate of 0.14 per dB) and follows (largely insignificant) results in this study. Based on auxiliary models, if noise in green open spaces is not explicitly taken into account, the direct negative effect of noise increases from 0.088% to 0.116% per dB (mean estimates which are not significant on conventional levels) which suggests some portion of the indirect effect is captured in standard analyses, but not all of it. While the effect of noise reduction on parks might seem rather low, it should be noted it is an indirect benefit of a policy aiming primarily at other objectives.

The indirect channel of costs of noise in green open spaces values is non-negligible and actually of the same magnitude as the direct effect. This cost is also not uniformly distributed across space. Decreasing noise in green open spaces would have heterogeneous effect on property prices given local accessibility of green spaces and their exposure to noise. Heterogeneity of the effect when noise decreases by 2 dB is shown on Fig. 3.

5. Discussion and conclusions

The results from both cross-sectional and quasi-experimental hedonic models confirm negative effect of noise on green open spaces' amenity value. Baseline estimates from the cross-sectional analysis show increasing size of quiet green open spaces with noise levels below 60 dB by 10% increases value of local apartments by 0.05%. Similar results, although of higher magnitudes, are found in the quasi-experimental design exploiting change in noise caused by transport network improvements.

Analysis of the effect of noise on perceived quality of green open spaces inferred from the quantitative spatial model reveals comparably robust evidence. When analysing data using individual green open spaces as observations, increasing size of quiet parts of green open spaces by 10% increases their quality by 1.2%. The magnitude is roughly one third smaller if individual apartments are used as observations.

Hypothetical policy reducing the speed limit from 50 km/h to 30 km/h with a subsequent decline of noise by 2 dB has been evaluated. Due to the lowered noise, size of quite green open spaces would on average increase by 1.1 hectare, or by 0.4 log points. Such change in area of accessible quiet green open spaces is associated with an increase of apartments' value by 0.2%, which is about the same magnitude as direct effect of noise decline at the apartments' location.

I analysed the city of Prague, Czech Republic, and this paper cannot provide evidence to what extent the results are transferable to other countries, but based on similarity of Prague to other OECD metro areas, it is more likely the results are more relevant for Central-West continental Europe.[16] This however does not mean the noise does

[15] The analysis is predominantly based on pre-covid data (with an exception of Public participation GIS survey data collected between April and September 2021), but it seems the results should hold even for the post-covid period. Ugolini et al. (2020) analysed use of green open spaces during the early wave of covid in Europe. They admit the benefits of green open spaces could be amplified during the crisis. The pattern of green open spaces' use changed especially in hardly-hit countries such as Spain and Italy, where number of people visiting green open spaces dropped, likely due to the policy restrictions on mobility, and as a result people in these countries missed green open spaces the most. They also conclude the need for outdoor recreation did not disappeared as people prioritized spending time outdoors. González-Marín and Garrido-Cumbrera (2024) analysed 31 articles studying change of perception of green open spaces during covid. Most of evidence shows there was increase in use of green open spaces and interest in nature and they concluded appreciation of green open spaces increased, especially if local policies substantially restricted mobility. Available evidence therefore shows the value of green open spaces rather increased, if anything.

[16] See section Similarity of Prague to other OECD Metro areas in Online appendix for more details.

not decrease amenity value of green open space in Americas, Asia or Australia. Cities there are just different from Prague and applying conclusions from this paper there should be done with caution.

This paper studied interaction of green open space provision with low levels of noise, extending existing evidence of green open spaces' interaction with crime levels (Albouy et al., 2020; Troy and Grove, 2008) and neighbourhood characteristics and demographics (Anderson and West, 2006). Future research could further investigate interaction of accessible green open spaces' size with overall quality or capital intensity to find to what extent these are substitutes or complements. This would be particularly policy-relevant in large cities where land is scarce and expensive. Additionally, this paper has focused on the city of Prague, a fairly large continental European city, and it would be informative to investigate if results would hold in smaller or less dense cities, or cities in developing countries.

Declaration of competing interest

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

Appendix A. Online appendix

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.124594.

Data availability

The code is available on request.

References

Ahlfeldt, G.M., Redding, S.J., Sturm, D.M., Wolf, N., 2015. The economics of density: Evidence from the Berlin wall. Econometrica 83 (6), 2127–2189.

Albouy, D., Christensen, P., Sarmiento-Barbieri, I., 2020. Unlocking amenities: Estimating public good complementarity. J. Public Econ. 182, 104110.

Anderson, S.T., West, S.E., 2006. Open space, residential property values, and spatial context. Reg. Sci. Urban Econ. 36 (6), 773–789.

Babisch, W., 2008. Road traffic noise and cardiovascular risk. Noise Health 10 (38), 27–33.

Brander, L.M., Koetse, M.J., 2011. The value of urban open space: Meta-analyses of contingent valuation and hedonic pricing results. J. Environ. Manag. 92 (10), 2763–2773.

Carles, J.L., Barrio, I.L., De Lucio, J.V., 1999. Sound influence on landscape values. Landsc. Urban Plan. 43 (4), 191–200.

Cho, S.-H., Poudyal, N.C., Roberts, R.K., 2008. Spatial analysis of the amenity value of green open space. Ecol. Econom. 66 (2–3), 403–416.

Czembrowski, P., Kronenberg, J., 2016. Hedonic pricing and different urban green space types and sizes: Insights into the discussion on valuing ecosystem services. Landsc. Urban Plan. 146, 11–19.

Czembrowski, P., Kronenberg, J., Czepkiewicz, M., 2016. Integrating non-monetary and monetary valuation methods–softgis and hedonic pricing. Ecol. Econom. 130, 166–175.

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

Desarnaulds, V., Monay, G., Carvalho, A., 2004. Noise reduction by urban traffic management. In: Proceedings ICA 2004.

Gidlöf-Gunnarsson, A., Öhrström, E., 2010. Attractive "quiet" courtyards: a potential modifier of urban residents' responses to road traffic noise? Int. J. Environ. Res. Public Health 7 (9), 3359–3375.

González-Marín, A., Garrido-Cumbrera, M., 2024. Did the COVID-19 pandemic influence access to green spaces? Results of a literature review during the first year of pandemic. Landsc. Ecol. 39 (2), 23.

Greene, W.H., 1990. Econometric Analysis. Macmillan.

Hanauer, M.M., Reid, J., 2017. Valuing urban open space using the travel-cost method and the implications of measurement error. J. Environ. Manag. 198, 50–65.

Heblich, S., Redding, S.J., Sturm, D.M., 2020. The making of the modern metropolis: evidence from London. Q. J. Econ. 135 (4), 2059–2133.

Héritier, H., Vienneau, D., Foraster, M., Eze, I.C., Schaffner, E., de Hoogh, K., Thiesse, L., Rudzik, F., Habermacher, M., Köpfli, M., et al., 2019. A systematic analysis of mutual effects of transportation noise and air pollution exposure on myocardial infarction mortality: a nationwide cohort study in Switzerland. Eur. Heart J. 40 (7), 598–603.

IPR Praha, 2017. Územně analytické podklady hlavního města prahy, 2016.

Ives, C.D., Oke, C., Hehir, A., Gordon, A., Wang, Y., Bekessy, S.A., 2017. Capturing residents' values for urban green space: Mapping, analysis and guidance for practice. Landsc. Urban Plan. 161, 32–43.

Melichar, J., Kaprová, K., 2013. Revealing preferences of prague's homebuyers toward greenery amenities: The empirical evidence of distance–size effect. Landsc. Urban Plan. 109 (1), 56–66.

Merchan, C.I., Diaz-Balteiro, L., Soliño, M., 2014. Noise pollution in national parks: Soundscape and economic valuation. Landsc. Urban Plan. 123, 1–9.

Monte, F., Redding, S.J., Rossi-Hansberg, E., 2018. Commuting, migration, and local employment elasticities. Am. Econ. Rev. 108 (12), 3855–3890.

Morawetz, U.B., Klaiber, H.A., Zhao, H., 2024. The impact of traffic noise on the capitalization of public walking area: A hedonic analysis of vienna, Austria. J. Environ. Manag. 353, 120060.

Moudon, A.V., 2009. Real noise from the urban environment: how ambient community noise affects health and what can be done about it. Am. J. Prev. Med. 37 (2), 167–171.

Nelson, J.P., 2008. Hedonic property value studies of transportation noise: aircraft and road traffic. In: Hedonic Methods in Housing Markets. Springer, pp. 57–82.

Panduro, T.E., Jensen, C.U., Lundhede, T.H., von Graevenitz, K., Thorsen, B.J., 2018. Eliciting preferences for urban parks. Reg. Sci. Urban Econ. 73, 127–142.

Pánek, J., Barvíř, R., Koníček, J., Brlík, M., 2021. The emotional map of prague–data on what locals think about the czech capital? Data Brief 39, 107649.

Paunović, K., Jakovljević, B., Belojević, G., 2009. Predictors of noise annoyance in noisy and quiet urban streets. Sci. Total Environ. 407 (12), 3707–3711.

Rossi, I.A., Vienneau, D., Ragettli, M.S., Flückiger, B., Röösli, M., 2020. Estimating the health benefits associated with a speed limit reduction to thirty kilometres per hour: A health impact assessment of noise and road traffic crashes for the swiss city of lausanne. Environ. Int. 145, 106126.

Smith, V.K., Kaoru, Y., 1990. What have we learned since hotelling's letter?: A meta-analysis. Econom. Lett. 32 (3), 267–272.

Troy, A., Grove, J.M., 2008. Property values, parks, and crime: A hedonic analysis in baltimore, MD. Landsc. Urban Plan. 87 (3), 233–245.

Ugolini, F., Massetti, L., Calaza-Martínez, P., Cariñanos, P., Dobbs, C., Ostoić, S.K., Marin, A.M., Pearlmutter, D., Saaroni, H., Šaulienė, I., et al., 2020. Effects of the COVID-19 pandemic on the use and perceptions of urban green space: An international exploratory study. Urban For. Urban Green. 56, 126888.

Ugolini, F., Massetti, L., Calaza-Martínez, P., Cariñanos, P., Dobbs, C., Ostoić, S.K., Marin, A.M., Pearlmutter, D., Saaroni, H., Šaulienė, I., et al., 2022. Understanding the benefits of public urban green space: How do perceptions vary between professionals and users? Landsc. Urban Plan. 228, 104575.

Whitehead, J.C., Pattanayak, S.K., Van Houtven, G.L., Gelso, B.R., 2008. Combining revealed and stated preference data to estimate the nonmarket value of ecological services: an assessment of the state of the science. J. Econ. Surv. 22 (5), 872–908.

Yannis, G., Michelaraki, E., 2024. Review of city-wide 30 km/h speed limit benefits in europe. Sustainability 16 (11), 4382.

Zhang, X., Melbourne, S., Sarkar, C., Chiaradia, A., Webster, C., 2020. Effects of green space on walking: Does size, shape and density matter? Urban Stud. 57 (16), 3402–3420.