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# Planning for green infrastructure: The spatial effects of parks, forests, and fields on Helsinki's apartment prices

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ABSTRACT

As the importance of urban green spaces is increasingly recognised, so does the need for their systematic placement in a broader array of socioeconomic objectives. From an urban planning and economics perspective, this represents a spatial task: if more land is allocated to various types of green, how do the economic effects propagate throughout urban space? This paper focuses on the spatial marginal effects of forests, parks, and fields and estimates spatial hedonic models on a sample of apartment transactions in Helsinki, Finland. The results indicate that the capitalization of urban green in apartment prices depends on the type of green, but also interacts with distance to the city centre. Additionally, the effects contain variable pure and spatial spillover impacts, also conditional on type and location, the separation of which highlights aspects not commonly accounted for. The planning of green infrastructure will therefore benefit from parameterizing interventions according to location, green type, and character of spatial impacts.



## 1. Introduction: The Spatial Economic Context of Implementing Urban Green

Green infrastructure (GI), with its capacity to provide ecosystem services (ES) in a comprehensive manner across an urban area, has been proposed as a key element in sustainable urban planning, as well as in adaptation and resilience to the effects of climate change (Renaud et al., 2013; European Commission, 1994, 2011, 2013; IPCC, 2012; European Environment Agency, 2011). From a rational planning perspective, the implementation of GI in cities represents the task of modifying a tightly interdependent spatial system, where the typical underutilization of natural areas needs to be addressed in a way that urbanization's fundamental non-ecological benefits are also maintained. Additionally, since the urban economic system is as sensitive to land use choices as the provided mix of ES is, the further question arises of knowing the differences between the economic effects of alternative green solutions. Besides planned spatial interventions, the above questions are valid also in the context of unplanned changes in the natural stock of an area, e.g., due to species changes following gradual change in climate conditions or one-time extreme weather events.[1]

In practice, the systematic implementation of GI implies trade-offs with other urban functions, and poor evaluation of green interventions in relation to a broader array of socioeconomic objectives may bring adverse effects (Wolch et al., 2014; Perino et al., 2014). These relate to the fact that the configuration of urban land use follows a specific spatial optimization logic. In order to maintain a sufficient amount of agglomeration benefits, the allocation of space to highly productive and therefore competitive functions (e.g., housing, public services, and jobs) is favoured and, in turn, functions typically regarded as less competitive—including ecosystems—tend to be minimized, substituted, or expelled. So, in theory, the relative location and size of objects matter greatly for the socioeconomic prosperity of cities, since this spatial logic has historically delivered fundamental benefits, such as optimal provision of services and employment, tight social networks, and efficient distribution and exchange of goods. The need to reconsider this logic relates to its inherent externalities (e.g., pollution, flooding and inadequate handling of storm water, noise, health effects), the effects of which are exacerbated by the changing climate. Ultimately, the issue at stake is integration and evidence-based decision support. Even though the importance of GI is obvious, it is not as straightforward to understand what the increased allocation of space to previously expelled, space-competing functions entails for the urban economy.

The above questions involve phenomena at multiple spatial scales (James et al., 2009). This study focuses on finer scales and on plannable features inherent to apartment properties and their immediate surroundings. The study assumes that the spatial effects of urban green as measured in the housing market are useful in understanding trade-offs involved in the implementation of GI at fine spatial scales. The analysis estimates spatial hedonic models on a sample of apartment

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[1] An example is a recent drought in Helsinki that resulted in the loss of pines and their replacement either by species that are more heat-resistant, or by empty land and more droughts.

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transactions in Helsinki, Finland for the years 2000–2011. Firstly, the marginal effects of three types of green spaces (forest, park, and field) and their interaction with distance to the city centre are estimated and compared. Subsequently, the spatial spillover impacts (direct, indirect, and total) for the capitalization of forests, parks, and fields in apartment prices are calculated. These spillovers are qualitatively different from distance decay (from a green space) or geographically variable effects. They introduce an additional policy-relevant aspect, indicating the extent to which the benefits of a certain green type remain at (or originate from) the implementation location or diffuse to (and from) neighbouring ones. The focus on apartment prices is motivated in light of sustainable urban growth and mixed, denser solutions for housing, which almost invariably imply apartment solutions for the urban population. The following section discusses in brief the urban economic context of green amenities, overviews past hedonic valuation studies, and explains the focus on specific spatial effects.

## 2. Urban Green in Housing Price Formation and Differentiation

The provision of multiple (Davies et al., 2011; Givoni, 1998) and often non-substitutable (Hauru et al., 2012) ES by green spaces makes them influential amenities in the urban economic context. As such, their participation in the formation of residential property value can be approached by referring to a residential location model (Muth, 1969; Mills, 1967; Alonso, 1964), modified to reflect the structural role of natural amenities. Brueckner et al. (1999) show that, in addition to transportation cost and preferences on dwelling type and size, the spatial variation of amenities will co-determine the equilibrium outcome. Households seek to locate near exogenous natural and historical amenities, and the wealthy will typically outbid the rest for locating near these amenities. The outcome of this process is reflected in the observed morphology of housing prices; high values are typically associated with amenity-rich locations, such as the urban core, green spaces, and coastline.

Empirically, the participation of natural amenities in price formation and differentiation is detected in realized housing market transactions by estimating the sensitivity of property prices towards the quantity, type, and quality of amenities. For ecological amenities, De Groot et al. (2002) and Bateman et al. (2010) enumerate methodologies for linking ES to monetary value, with hedonic analysis being the most relevant approach in the housing market. Hedonic price theory suggests that housing is a composite commodity, representing for consumers more than just a shelter; proximity to amenities and services are examples of other attributes bundled together in housing. By estimating the market price of dwellings as a function of their attributes, it is possible to derive an implicit value for each attribute (Brueckner, 2011; Sheppard, 1999; Dubin, 1988; Quigley, 1982; Rosen, 1974). The estimated coefficients of the attributes are interpreted as their marginal values or effects. By analysing the variation of the type, quantity, and quality of hedonic attributes in relation to the corresponding variation in property prices, inferences can be made about the implicit value and relative importance that consumers tend to attach to ecological amenities, as well as the willingness to pay (WTP) for them (Freeman et al., 2014). The estimated effects are also useful in comparing different types of urban green with respect to relative importance and implicit value, as different types of green can be approached as distinct hedonic attributes.

In Finland, Tyrväinen (1997) reports that a 100 m increase in the distance of a dwelling to wooded recreation areas decreases its market price/m$^2$ by 42 FIM (€ 7.14) in the city of Joensuu, while Tyrväinen and Miettinen (2000) report that a 1 km increase in the distance of a dwelling to a forested park decreases its market price by 5.9% on average and a direct view to a forested area increases price by 4.9% in the city of Salo. In both studies as well as in international literature (e.g. Czembrowski and Kronenberg, 2016), the authors observe a notable dependence of the estimations on the type of green and the variable that represents it. The consensus in literature is that urban green is positively valued in the housing market; the meta-analysis studies of Brander and Koetse (2011), Perino et al. (2014), and Siriwardena et al. (2016) provide thorough summaries.

As the housing market has a strong geographical dimension, the hedonic approach is often augmented, among others, with the concepts of spatial non-stationarity and spatial spillovers. Spatial non-stationarity concerns the cases where regression coefficients vary across geographical space (Bivand et al., 2008; Lloyd, 2007; Schabenberger and Gotway, 2005; Fotheringham et al., 2002). For the present context, this suggests that the marginal effects of green will vary across different parts of the city and may be altogether zero in some locations, from a global point of view, regardless of the local distance decay function to individual green patches (e.g. Cho et al., 2011). For instance, empirical studies report a general decrease in the value of formal green patches as population density decreases (Brander and Koetse, 2011) or ownership of private green spaces increases (Tu et al., 2016). In addition, the first law of geography (Tobler, 1970; Miller, 2004) suggests that geographical locations are in fact interdependent so that a change in one location will affect neighbouring locations and vice versa. This implies that the marginal effects measured in hedonic regressions are the combination of pure effects due to the characteristics of a given property and spatial spillover effects due to interaction with neighbouring properties (LeSage and Pace, 2009; Anselin, 2003, 1995, 1988).

In summary, considering green spaces in connection to the spatial morphology of property prices, and drawing from the discussed literature, the estimations of this paper aim to explore the following three spatial effects of green interventions. Firstly, different types of green should be explored in more detail as amenities that are distinct from each other, which may entail different price effects, too. Secondly, different parts of the city, notably the core and periphery, are so fundamentally different, that a given solution will have geographically variable effects. Thirdly, as cities are systems of spatially interdependent locations, a green intervention at one location affects the rest of the system and vice versa. Green interventions will thus generate spatial spillover effects that propagate throughout the city in varying intensities and through varying channels. The first assumption is tested by estimating the marginal effects of distances to forests, parks, and fields; the second by including an interaction of the effects with distance to city centre; the third by separating pure from spatial spillover impacts.

## 3. Models and Assumptions

The particular view of green space assumed in the previous sections motivates the use of spatial regression models as better equipped to provide insights to the stated urban planning questions than non-spatial models. In addition, spatial regression models are capable of addressing estimation issues that are characteristic to spatial data analysis and hedonic datasets. Details about the foundations, methodology, and application of such models are found, among others, in Gerkman (2012), Anselin et al. (2010), LeSage and Pace (2009), Anselin (2003, 1988), and Dubin (1988).

Unobserved effects that exhibit spatial dependency are frequent in hedonic analysis due to hard-to-operationalize or non-decomposable spatial concepts like neighbourhood prestige or (un)attractive design. In that case, the residuals of ordinary least squares (OLS) estimations will be spatially autocorrelated and violate the i.i.d. error assumption. The first-order autoregressive spatial error model (SEM) addresses this problem by separating the residuals into a spatially autocorrelated component and an uncorrelated random error (model 1):

$$\mathbf{y} = \mathbf{X}\beta + \lambda\mathbf{W}\mathbf{u} + \epsilon, \tag{1}$$

where $\mathbf{X}$ is a matrix of hedonic attributes, $\mathbf{W}$ a spatial weights matrix, $\mathbf{Wu}$ a spatially autocorrelated error term, $\epsilon$ a random error term, and $\beta$, $\lambda$ coefficients. The interpretation of coefficients in the SEM is the same as in OLS, while the spatial error term is usually seen as an uninterpretable instrument that clears residuals from spatial autocorrelation.

The assumption of spatial non-stationarity in the effects of green across the city can be explored by checking whether the magnitude of the price effect of distance to green is conditional on distance to the city centre. It is assumed that inserting a linear interaction term for each ecological variable in model 1 will serve this purpose. If **c** denotes distance to the city centre (CBD) and $\mathbf{g}_j$ distance to green with $j = \{$forest; park; field$\}$, '$\mathbf{g}_j$*$\mathbf{c}$' denotes the interaction of the two variables, and $\zeta$, $\eta$, $\kappa$ are regression coefficients for the two new variables and their interaction term, model 1 can be re-formulated as:

$$\mathbf{y} = \mathbf{X}\beta + \left\{\zeta\mathbf{c} + \eta\mathbf{g}_j + \kappa\left(\mathbf{g}_j * \mathbf{c}\right)\right\} + \lambda\mathbf{W}\mathbf{u} + \epsilon, \tag{2}$$

In the occasions that the spatial common factor hypothesis is satisfied, SEMs are nested into a larger model, which includes spatially lagged forms of the dependent and independent variables. The resulting specification is called the spatial Durbin model (SDM) and is used to separate and simulate spatial impacts important for urban planning and decision-making:

$$\begin{aligned}\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\beta + \vartheta\mathbf{W}\mathbf{X} + \left\{\zeta\mathbf{c} + \eta\mathbf{g}_j + \kappa\left(\mathbf{g}_j * \mathbf{c}\right)\right\} \\ + \left\{\varphi\mathbf{W}\mathbf{c} + \xi\mathbf{W}\mathbf{g}_j + \omega\mathbf{W}\left(\mathbf{g}_j * \mathbf{c}\right)\right\} + \epsilon,\end{aligned} \tag{3}$$

where the endogenous term **Wy** is the spatially lagged form of the dependent variable, **WX**, **Wc**, $\mathbf{Wg}_j$, $\mathbf{W}(\mathbf{g}_j*\mathbf{c})$ are the spatially lagged forms of the independent variables, and $\vartheta$, $\varphi$, $\xi$, $\omega$ are coefficients for the newly introduced terms.

The difference of SDM model 3 from SEM model 2 is the replacement of the spatially autocorrelated residual with the endogenous lagged form of the dependent variable and exogenous lagged forms of all the independent variables. In a sense, the SDM attempts to identify the unobserved spatial interaction captured in SEM's spatial error term by estimating spatially weighted effects of the dependent and each of the independent variables.

However, the estimated marginal effects of the hedonic attributes of model 3 are not interpretable at their face value, because the specification includes the dependent variable in both sides of the equation. Solving for the dependent variable shows that the effect of each variable on $y$ consists of 'pure' and 'spatial spillover' effects, that is, of the impact of a region's own attributes plus the cumulative impacts spilling over from the attributes of neighbouring regions. LeSage (2008) and LeSage and Pace (2009) propose to render the coefficients interpretable by separating them into direct, indirect, and total impacts, depending on the geographical origin of the effect. Thus, if the interest is the marginal effect $dy/dx$ in a typical region of an inter-dependent spatial system, then: direct is the effect due to changing $x$ only at that particular region; indirect is the effect due to changing $x$ in the neighbouring regions; and total is the effect due to a simultaneous system-wide change in $x$ (LeSage, 2008). A region in the present case is interpreted as an individual property and its immediate vicinity.

The use of spatial matrix $W$ for identifying and estimating spatial effects means that explicit assumptions about space and spatial interaction need to be made. In this study, the notion of 'space' is operationalized as the 1st order von Neumann neighbourhood of each property in the sample. Pre- and post-estimation specification tests confirmed the applicability of SEM model 2 to the sample, while the spatial common factor hypothesis verified that model 2 can be expressed as SDM model 3.

## 4. Data

The analysis has used approximately 44,300 apartment transaction records from the municipality of Helsinki ($\approx$ 536,000 inhabitants, 21,655 ha). The data record the selling price and other monetary characteristics of the property together with its postal address and several structural characteristics.[2] The monetary variables (price, debt, maintenance cost) were de-trended by adjusting for inflation with 2011 as the reference year and normalized to represent $m^2$ figures. The geographical coordinates of the observations were retrieved from the street address by a geo-reference operation, and land use and technical infrastructure maps were used to calculate additional hedonic variables that measure the distance of each property to ecological attributes and main transport lines. The procedure produced what Dubin (1988) describes as the structural, locational and neighbourhood characteristics of the dwelling, suitable for the estimation of spatial hedonic functions. Table 1 describes the analysed variables; the environmental variables are discussed in more detail in the following paragraphs.

The ecological variables were constructed by associating the geocoded transaction points to information extracted by land use maps. More specifically, the 10 m SLICES land use/cover product by the National Land Survey of Finland was used to extract three main classes: forest, park, and field. The names are translations from Finnish, while the land uses they represent are predefined by the data provider. Forests refer to predominantly tree-covered patches and aggregate various classes of tree species. Parks refer to patches with a varying mixture of natural and man-made features that include, for instance, trees, bushes, lawn, ground, and paved or unpaved pathways. Fields refer to predominantly agricultural fields and is an aggregate class including any type of crop and activity status (actively cultivated or inactive). Other natural land uses such as bare rock and soil, sand, gravel, peats, and wetlands are not included in the three classes. Fig. 1 provides indicative examples of the three land uses.

Following the extraction of forest, park, and field patches, maps of the Euclidean distance of every location of the metropolitan region to the perimeter of these patches were created. The procedure was repeated for the land use maps of years 2000, 2005, and 2010 and each observation point was overlaid on the distance map nearest to transaction year, in order to capture changes in the land use composition of the urban region. Distance to the coastline was calculated in a similar way. The spatial resolution of the land use maps implies that a patch of land has to be larger than 10 by 10 $m^2$ to be detected and classified. The implication for the analysed dataset and the interpretation of the estimations is that distances to green areas should be understood as distances to sufficiently large and therefore identifiable by land cover/use maps patches of green. Thin rows of trees are absorbed to the surrounding land cover type, if they are <10 m wide, so that the distance of properties to road-side trees and then to a park is essentially distance to a park only.

A lot size variable is included to ensure that the ecological coefficients do not reflect the effect of large lots belonging to the property. Such a risk is introduced due to the high spatial resolution of the land use data, where the measured distances to green spaces may also include patches that belong to the parcels of the dwellings. In addition to including a lot size variable, the land use data used in this study pose a reduced risk of suffering from the above issue. These data do not classify lots or parcels belonging to residential properties as natural green spaces. Such patches are classified as man-made residential land use. Although data capture, classification, and spatial averaging errors in the source maps cannot be ruled out, this risk is further minimized by the fact that the analysed dwellings are apartments in an intensely quality-checked area (the capital city), and thus their lots are classified with high certainty as residential. It is thus reasonable to assume that the captured marginal effects relate only to distinct and formally designated green spaces.

Similarly, three variables measuring distance to major transport infrastructure are included to ensure that the estimations do not suffer

[2] These data are voluntarily collected by a consortium of Finnish real estate brokers and the dataset is refined and maintained by the VTT Technical Research Centre of Finland Ltd. As not all real estate agencies participate, this dataset represents a sample (albeit rather large) of the total volume of transactions.

**Table 1**
The variables of the analysis with mean values.

| Variable | Description | Unit | Mean |
|---|---|---|---|
| PRICE | Selling price per $m^2$, 2011 prices | € thousand per $m^2$ | 3.302 |
| DEBT | Debt component[(a)], 2011 prices | € thousand per $m^2$ | 0.187 |
| MAINT | Monthly maintenance cost, 2011 prices | € per $m^2$ | 3.245 |
| FLOORSP | Floor-space | $m^2$ | 56.2 |
| ROOMS | Rooms, excluding kitchen | Multinomial (1–9 rooms) | 2.169 |
| FLOOR | The floor on which the apartment is situated | Multinomial (1st – 9th floor) | 2.99 |
| AGE | Difference between selling and construction year | Years | 48.24 |
| BADCND | Bad condition | Dummy (1: bad, 0: otherwise) | 0.06 |
| AVGCND | Average condition | Dummy (1: average, 0: otherwise) | 0.328 |
| LOTSIZE | Lot size | $m^2$ | 1842 |
| CBD | Distance to the central business district[(b)] | Kilometres | 5.376 |
| RLINE | Distance to railway track | Kilometres | 1.259 |
| MLINE | Distance to above-ground metro line | Kilometres | 2.515 |
| MJROAD | Distance to major roads | Kilometres | 0.537 |
| SEA | Distance to the coastline | Kilometres | 1.26 |
| FOREST | Distance to the nearest forested area | Kilometres | 0.088 |
| PARK | Distance to the nearest park | Kilometres | 0.294 |
| FIELD | Distance to the nearest field | Kilometres | 1.294 |

[(a)] Properties in apartment blocks or row houses are usually managed by a housing cooperative/committee. Large maintenance tasks (e.g., roof, piping, or structural renovations) are undertaken by the housing committee and financed by a dedicated loan. The property's debt component is the portion of that loan that corresponds usually to the size of the property; it bounds the property rather than the owner, and passes from one owner to the next when the property is sold.
[(b)] CBD has been defined as the point in Helsinki's centre with the highest density of commercial establishments.

from the omission of noise or air pollution effects. The included variables measure distances to rail lines (which service commuter and long distance trains), above-ground metro lines (which service the segment of Helsinki's metro exposed to the surface and surrounding properties), and main road transport lines (which include type I and II highways and multilane roads). Remaining problems of spatially correlated omitted variables are addressed by the spatial models described in Section 3, which by definition clear estimates from this type of bias.

While the robustness of the housing transaction data has greatly benefited this study, similar availability cannot be presupposed in the developing world, where urban ES is a key issue. Assuming that transaction microdata is inaccessible or unsystematically collected, a way out is the use of aggregate, social media, or soft-GIS information. The models of this study are applicable to aggregate data, as long as the interpretation and policy recommendations avoid the ecological fallacy and focus on neighbourhoods rather than individual properties. Alternatively, the analysis of social media data is increasingly used in conservation and ES research (Wood et al., 2013; Di Minin et al., 2015). Typical steps would be to access the public API's of social media platforms, extract or deduce relevant information, and proceed with spatial hedonic analysis. Lastly, soft-GIS uses crowd-sourced observations to collect valuation-relevant information that is unavailable via more conventional routes (Brown et al., 2014; Brown and Kyttä, 2014). A typical setup would be the creation of a web or mobile platform that asks residents to tag properties or locations with encoded or free-form information on the characteristics of locations and properties and/or their price level. The effectiveness of this approach largely depends on the available technical infrastructure, data sharing culture, and method used to convert qualitative to quantitative data; its success and accuracy, however, has been demonstrated (Haklay and Weber, 2008; Haklay, 2010). In the last two cases variables used in this study but unavailable elsewhere can be produced by processing the mined information with publicly available or custom-made inference algorithms. Well-trained inference algorithms—using, for instance fuzzy logic, neural networks, or hybrid approaches—have the capacity to infer price levels and other difficult-to-collect quantities from sparse or qualitative information.

## 5. Marginal Effects and Urban-core-to-fringe Gradients

SEM model 2 was estimated firstly on the full sample (2000 — 2001) and subsequently on six biannual subsets (2000–01; 02–03; 04–05; 06–07; 08–09; 2010–11). The estimations were implemented in the 'R' software (R Core Team, 2016) in the spatial econometrics module 'spdep' (Bivand et al., 2016). The 'GeoDa' software (Anselin et al., 2005) was used to generate the spatial weights files.

The full-sample estimation (Table 2) explained 78% of price variation and returned the expected signs for all hedonic coefficients, except for that of distance to a forest. An increase in the debt and maintenance costs and a decrease in the condition of the property decreases price/$m^2$. Additional rooms have a negative effect, reflecting the diminishing marginal utility of additional units of space. Increase in the property's age decreases price until historical status becomes relevant and price increases again. The yearly dummy variables (omitted from Table 2) are

**Fig. 1.** Examples of green areas classified as forest (left), field (middle), and park (right).

**Table 2**
Spatial error estimation results, full sample.

| Coef. (std. error) | | | | | | | |
|---|---|---|---|---|---|---|---|
| INTERCEPT | 4.301*** | $[AGE]^2$ | 0.000*** | LOTSIZE | 0.000 | FOREST | 0.331*** |
| | *(0.036)* | | *(0.000)* | | *(0.000)* | | *(0.090)* |
| DEBT/m$^2$ | −0.615*** | FLOOR | 0.067*** | RLINE | 0.050*** | FOREST ∗ CBD | 0.004 |
| | *(0.008)* | | *(0.002)* | | *(0.005)* | | *(0.024)* |
| COST/m$^2$ | −0.012** | BADCOND | −0.370*** | MLINE | 0.064*** | PARK | .−0.509*** |
| | *(0.002)* | | *(0.011)* | | *(0.004)* | | *(0.065)* |
| ROOMS | −0.163*** | AVGCOND | −0.234*** | MJROAD | 0.120*** | PARK ∗ CBD | 0.061*** |
| | *(0.003)* | | *(0.005)* | | *(0.016)* | | *(0.007)* |
| AGE | −0.029*** | CBD | −0.173*** | COAST | −0.096*** | FIELD | 0.0148*** |
| | *(0.001)* | | *(0.005)* | | *(0.010)* | | *(0.011)* |
| | | | | | | FIELD ∗ CBD | −0.035*** |
| | | | | | | | *(0.003)* |
| N | 45,982 | Pseudo $R^2$ | 0.78 | | | | |

Notes:
1. Significance ranges: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.
2. The unit of the ecological independent variables is distance to the green feature in kilometres.
3. The unit of the dependent variable is the property's selling price in € thousand per square metre.

significant, indicating a drop in the average level of selling price/m$^2$ from 2000 to 2001, followed by an increase from 2002 onwards. Increased distance to the city centre and coastline decrease price, whereas lot size is not significantly different from zero. The coefficients of the proxies for noise and air pollution disamenities are significant; a 100-meter increase in distance to rails increases average m$^2$ price by 0.15%, while the corresponding increase for over-ground metro line is 0.19% and for major road is 0.36%.

The estimation supported the assumption of a CBD gradient in the marginal effects of parks and fields. Increased distance to a park decreases prices in the city centre, or, conversely decreasing the distance of a downtown property to a park increases its price, with the effect gradually declining as distance to the CBD increases. The maximum effect is estimated to a decrease of 1.5% in the m$^2$ price when distance to a park increases 100 m, which is in the same range to the effect of recreational forests in the study of Tyrväinen (1997) that reports a corresponding increase of 0.5% (after currency conversion and average price normalization). However, the respective amenities are not directly comparable beyond a loose association of recreation to both types. Increased distance to fields decreases price in the urban fringe, or conversely, decreasing the distance of a suburban property to fields increases its price. The maximum effect along this gradient is a decrease of 1.1% in m$^2$ price when distance to a field increases by 100 m.

The regression is problematic in understanding the effect of forests. It indicates that increased distance to a forest increases price throughout the city with no statistically significant CBD gradient. Interestingly, a similar result is reported by Tyrväinen (1997) for the effect of distance to forest parks, who attributed it to non-fulfilment of the conditions for capitalization (Starret, 1981) and to dweller preferences on the specific tree type in forest parks. Additionally, Tyrväinen (1997) and Tyrväinen and Miettinen (2000) note that samples that are aggregated from years with varying macroeconomic conditions may pose estimation problems. Table 3 indicates that the present sample does have such variations as indicated by the somewhat sharp fluctuations in regional unemployment rates.

This ambiguity with the effect of forests was resolved by repeating the estimations firstly on biannual samples and secondly on the full sample with a model that separates pure from spatial spillover effects. Both alternatives maintained similar coefficient values for parks, fields, and the remaining hedonic variables. The rest of this section discusses in more detail the effects of parks, forests, and fields as estimated on the biannual samples, while Section 6 discusses the separation of pure and spatial spillover effects in the full sample.

Fig. 2 summarizes the effects per green type as estimated in the biannual subsets, showing the variation between subsets and multiyear average. The full results are provided in Table A-1 of the Appendix A. The graphs display only the years in which both the maximum (minimum in the case of fields) marginal effect (FOREST, PARK, FIELD) and its interaction term (FOREST ∗ CBD, PARK ∗ CBD, FIELD ∗ CBD) were statistically significant at the 95% margin, so that the gradient effect $\eta \mathbf{g}_j + \kappa(\mathbf{g}_j * \mathbf{c})$ of model 2 can be discussed with certainty. The graphs indicate a clear urban-core-to-fringe gradient for the three green types, as well as different magnitudes and gradient slopes between types.

The maximum effect of distance to a forest or park is at the urban core, while that of distance to a field is in the urban fringe. On a multiyear average, the effect of a 100 m increase of distance to a forest is a decrease of 3.7% in price/m$^2$ at 0 km from the CBD, which gradually drops to zero at 6 km from the CBD. The maximum effect is close to that reported by Tyrväinen and Miettinen (2000), which corresponds to a 5.3% decrease in price/m$^2$ for a 100 m increase in distance to a forested area for the average floorspace of 90 m$^2$ of their sample. The difference in estimates may be attributed to the fact that the valuation of Tyrväinen and Miettinen (2000) was conducted on a sample of terraced apartments as opposed to block apartments in this study. Terraced houses in Finnish housing markets have higher m$^2$ price than block apartments and are typically associated with wealthier households; it is assumed that the difference between the two studies relates to the higher WTP of wealthier households for green amenities. The maximum effect of distance to a park is estimated to 1.8% at the CBD, gradually dropping to zero at approximately 8 km from the CBD. As in the full-sample regression, the slope of the gradient of distance to a field is reversed; the maximum effect is 0.8% in the urban fringe (indicatively at 15 km from the CBD) and gradually drops to zero at approximately 8 km from the CBD. The difference between these estimates and the estimates of the full-sample regression is small (0.3% for parks and fields), except of the notable difference in the forest effects.

**Table 3**
Regional unemployment rates in Helsinki's NUTS-3 administrative region during 2000–11.

| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| u % | 6.3 | 5.5 | 5.8 | 6.5 | 6.5 | 6.1 | 5.4 | 5.0 | 4.8 | 6.2 | 6.4 | 5.8 |

The estimated gradients show that at approximately 6 to 8 km from the CBD, the marginal value of forests and parks diminishes to zero, while that of fields rises from zero. The estimations return negative effects in areas further than 6–8 km from the CBD for forests and parks, and in areas closer than 8 km to the CBD for fields. This is due to the assumed unbounded linear form of the gradient; it is therefore interpreted not as an actual discount, but as zero benefit. The maps in Fig. 3 (reproduced in color in the article's electronic version and in greyscale in its paper version) display the multiyear mean gradients (black lines in Fig. 2) as surfaces over Helsinki's urban morphology and also indicate the spatial distribution of Helsinki's GI and densities of residential building stock.

The urban-core-to-fringe gradients in the coefficients of green spaces merit further attention. The empirical literature points to scarcity arguments to explain this feature and highlights the influence of suburban residential development dynamics.

The decline of the implicit price of urban green as population density decreases is reported in both the North American and European contexts (Brander and Koetse, 2011; Perino et al., 2014; Siriwardena et al., 2016). The gradient has been related to scarcity-demand (Siriwardena et al., 2016) or scarcity-crowdedness arguments (Brander and Koetse, 2011). As population density increases, so does built-up density, which—as implied by the land use component in the spatial equilibrium of the Alonso-Muth-Mills model—results in scarcer natural spaces, raising the value of remaining green patches. Population density is proxied here by distance to the CBD; the municipality of Helsinki (as opposed to the broader metropolitan region) is monocentric with a decline of population and built-up density as distance to the CBD increases (Fig. 3 bottom right). Furthermore, it is reasonable to assume that the (as yet) non-substitutable capacity of green spaces to correct the environmental externalities occurring in the central areas of urban agglomerations adds to a pure scarcity argument. The estimations indicate that the minimization of the marginal value of forests and parks starts at approximately 6 to 8 km from the CBD. In this zone, the older and denser parts of Helsinki transition to a sparser morphology with more abundant nature and less intense environmental externalities. The estimated decrease of value with increased distance to the CBD also relates to the contingent valuation study of Tu et al. (2016), which found that ownership of a private garden decreases the WTP for living closer to an urban park, which in this study relates to an increased likelihood of private garden or yard ownership, typically associated with mid-to-low density residential land uses.

The CBD gradient in the marginal price of fields follows the reverse trend and begins to rise at approximately the zone in which the marginal price of forests and parks is minimized. Although the location at which this gradient becomes nonzero positive may be explained by the fact that fields in Helsinki are only found starting from approximately this zone (Fig. 3 bottom left), it cannot explain the rising prices when moving deeper into the suburban zone. Historical data and exploratory land use – transport modelling (available by request) indicate that development is particularly active in this area and advances via the consolidation of existing built-up clusters and their expansion into forests and fields. The built-up expansion is constrained in the north by an administrative border that encircles the municipality and in the south by the already intensely developed central parts of the city.

Roe et al. (2004) show that agricultural land near new suburban housing developments is the most attractive price compensation feature for relocating households. This can explain the positive values estimated for fields in this study, as the main component of the variable is agricultural land. The maximum magnitude of the effect is comparable to that of urban parks, which, too, is in line with hedonic literature reporting that agricultural fields have the capacity to increase the prices of nearby properties as much as other types of green spaces (Ready and Abdalla, 2005).

The perceived value is, however, conditional on the development prospects of the agricultural patches (Roe et al., 2004) and home buyers place higher value on open space when it is perceived as conservable (Geoghegan, 2002; Irwin, 2002), also in Finland (Tyrväinen and Väänänen, 1998). Concerning agricultural fields in the urban fringe, a scarcity argument has been proposed elsewhere: the highest WTP for agricultural land is expected when most of it has been developed (Roe et al., 2004). Given these suggestions, the estimated gradient for fields may also be taken as an indicator of the perception of suburban apartment buyers about the surrounding fields, namely that they are perceived as already scarce (fairly accurately, as seen in Fig. 3) but likely preserved. Furthermore, these scarce patches are near the administrative limit of the municipality and most of them have a pronounced conservation flavour—being, among others, municipal farms or adjacent to the protected ecosystems of the nearby rivers—which may strengthen the perception of these fields as conservable. One can thus argue that these conservation perceptions function concurrently with the high value potential of agricultural fields discussed by Roe et al. (2004), and since the conservation areas are mostly located at the outer administrative limit of the municipality, they cause marginal prices to

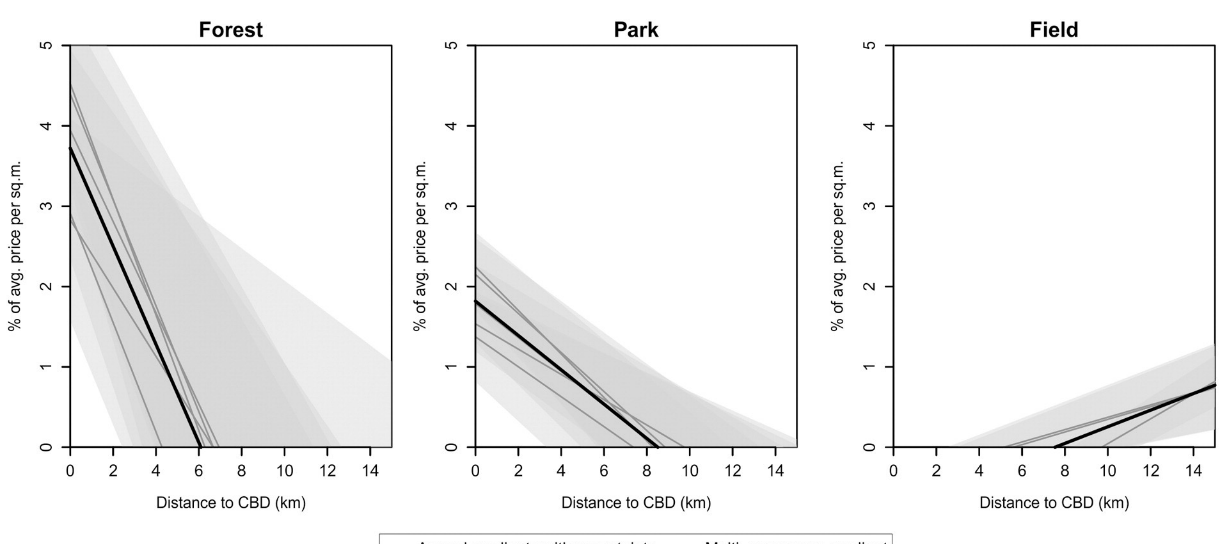


**Fig. 2.** Marginal effects and spatial gradients for forest (left), park (middle), and field (right). Grey lines and shaded areas denote the gradients and estimation uncertainty of statistically significant years. Black lines denote multi-year mean gradients.

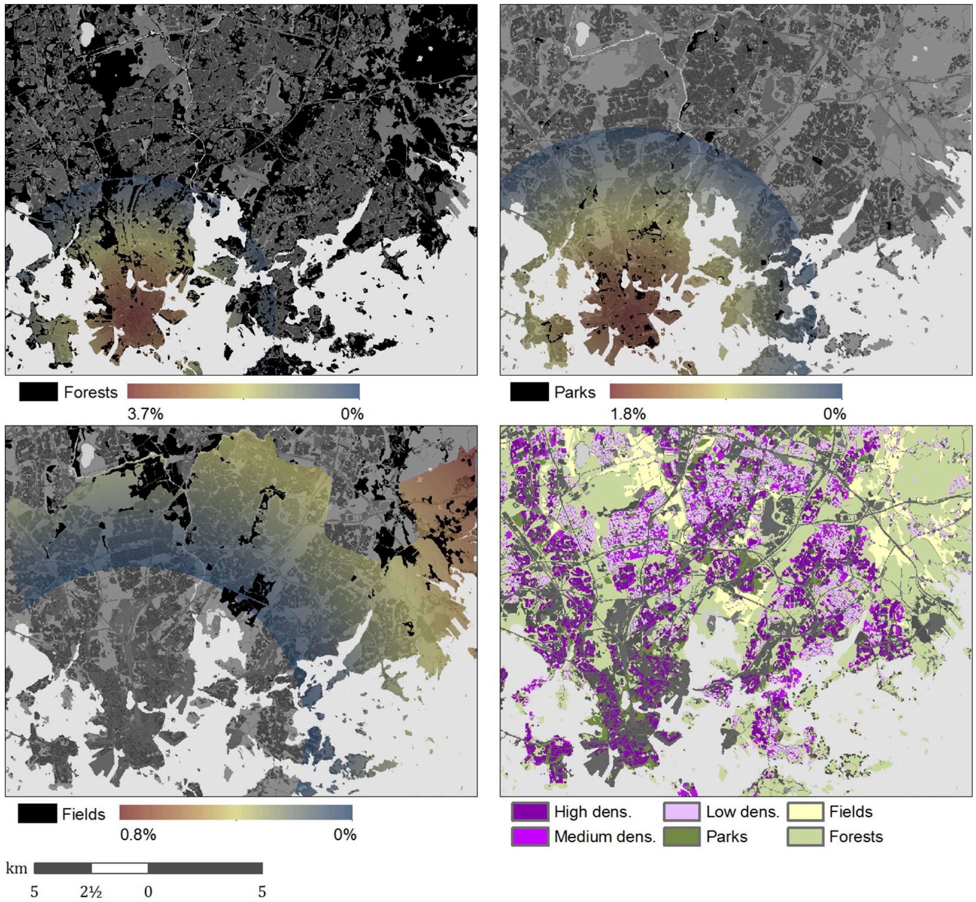


**Fig. 3.** Effect gradients of forested areas (top left), parks (top right), and fields (bottom left); each map also displays (in black) the spatial distribution of the respective green type. Helsinki's green infrastructure and residential densities are shown in the bottom right image.

gradually rise as properties approach this limit (i.e., with increased distance to the CBD).

Lastly, Ready and Abdalla (2005) report that when the alternative use of agricultural fields is low density residential, the patch does not affect the prices of nearby properties, whereas if the alternative is high density residential or commercial/industrial, it reduces prices of nearby dwellings. This is in line with the estimated gradient for fields. On one hand, moving closer to the CBD represents a higher likelihood of available land being converted to high density usage, represented here as a gradual drop to zero effect. On the other hand, the marginal price is estimated on apartment transactions, which are not the standard type of suburban development in Helsinki. As distance to the CBD increases, so does the likelihood of new development being low or medium density, which according to Ready and Abdalla (2005) means a higher expected value for agricultural fields.

The above discussion of the biannual estimates uses multiyear averages. The biannual variation in the magnitude and slope of the estimated effects is limited; in the maximum effect of distance to a forest it amounts to $\pm 1\%$, to a park $\pm 0.5\%$, and to a field it is negligible. Yet the temporal subsets eliminated the forest coefficient issue of the pooled sample while returning similar values for the rest of the effects. This feature is present also in regressions on single year samples, but could be attributed to small sample sizes. To check this, biannual samples (reported here) with large sample sizes (between approximately 5000 in 2000–01 and 10,000 in 2010–11) were constructed in order to rule out sample instability, but the temporal variation was retained. One could hypothesize that consumer confidence and purchasing power influences how much house buyers are willing to pay for green amenities. A competing hypothesis could be that perceptions about the present or future scarcity of the local natural environment might have influenced the measured marginal prices of distance to green. These hypotheses could not be explored here via, for instance, a second-stage hedonic analysis (Quigley, 1982; Brueckner, 2011).

While the temporal variation of the coefficients could be ruled out as instability, the negative amenity effect of forests in the pooled regression versus the positive effect in the biannual regressions is still an issue. This raises the question of why the same robust spatial specification produces contradictory conclusions about the effect of forests on temporally different samples. The following section presents a competing explanation for this ambiguity that focuses instead on the separation of pure from spillover effects.

## 6. Separating Pure and Spatial Spillover Impacts

While the hedonic valuation literature has been increasingly addressing the issue of spatially autocorrelated omitted variables via spatial specifications or other types of spatial controls (Kuminoff et al., 2010), contamination of the estimated effects by multiple waves of spatial spillover effects from neighbouring properties has not received much attention. As discussed in Section 3, in a spatially dependent market, the implicit price of an environmental amenity reflects not only the market transaction of a particular property (the typical hedonic valuation context); it may also contain the spillover of the same effect that diffuses from neighbouring properties.

In order to separate pure for spatial spillover effects, SDM model 3 was estimated as an alternative to SEM model 2 for the full 2000–2011 sample. Adapting LeSage (2008), and maintaining the interpretation of % changes in the $m^2$ price of a typical apartment, caused by a change in the distance to urban green, the spatial impacts are interpreted as follows. Direct are the price impacts of a change at the property itself, whereas indirect are the impacts that spillover from a change in neighbouring properties. If the change happens simultaneously in a city-wide fashion, this is reflected in the total impacts. The issue can be therefore approached by asking where a change happens and where the benefits go: at the property, neighbouring properties, or simultaneously everywhere.

Table 4 and Fig. 4 summarize the estimated spatial impacts. The estimation explained 79% of total price variation. The maximum direct impact of a 100 m increase of distance to a forest is a decrease in $m^2$ price by 1% at the urban fringe, gradually dropping to zero at approximately 9 km from the CBD; the maximum indirect impact is reverse with approximately 3.4% at the CBD, gradually dropping to zero at 4 km from the CBD; and the maximum total impact is 2% at the CBD, gradually dropping to zero at 3 km from the CBD. Concerning the effects of a 100 m increase of distance to a park, the maximum direct impact is 0.1% at the CBD, gradually dropping to zero at 3 km from the CBD; the maximum indirect impact is 2% at the CBD, dropping to zero at 10 km from the CBD; and the maximum total impact is 2.2% at the CBD, dropping to zero at 9 km from the CBD. The maximum direct impact of a 100 m increase in distance to a field is 2.5% at the urban fringe, gradually dropping to zero at 3 km from the CBD; the maximum total impact is 0.7% at the CBD, declining to zero at 8 km from the CBD; indirect impacts are negative and assumed as zero-benefit.

While the indirect and total impacts of forests are maximum at the CBD and declining farther away, their direct impact exhibits a gradient similar to that of fields and its sign at the CBD resembles that in the full-sample SEM model, which was taken as problematic. Given this evidence, however, it is reasonable to presuppose that the full-sample SEM model returned unexpected estimates for forests because it was unable to separate pure from spillover effects and the fact that indirect and direct impacts have opposite gradients.

The above figures indicate a few important differences in the spatial character of the marginal price effects of distance to forests, parks, and fields. Given the separation of pure and spillover effects, it is reasonable to suggest that decreased distances to all three green types capitalize positively in Helsinki's apartment prices, but only at the correct locations within the urban area and with a specific spatial impact character in mind. In particular, fields capitalize exclusively in the urban fringe and the effects concern exclusively changes at a certain property; spatial spillover of the price effects to/from neighbouring properties is zero and it takes a city-wide change (total impacts) to observe more widespread price changes. In contrast, parks capitalize exclusively at the city centre; the price effects are small at the concerned property and mostly spill over to (and from) neighbours. The capitalization of forests is double-natured as also found in Tyrväinen (1997); they capitalize at the concerned property only in the urban fringe, while the price effects in the urban core are spillovers to and from the neighbourhood.

Lastly, from a spatial policy viewpoint, the overlapping of the effect gradients is of interest. The gradients suggest that, all other things equal, certain zones are more flexible in the sense that more than one alternative green type can have positive price effects; in the zone of 0–4 km from the CBD the indirect effects of forests and parks overlap, while between 8 and 10 km the direct effects of forests and fields overlap. Nevertheless, as discussed previously, the spatial diffusion character of capitalization also varies spatially. The overlapping of impacts should not be therefore understood as an indication of substitutability, but rather as a way to correct the inability of one type of green to produce certain effects by complementing it with the ability of another type. This is evident, for instance, in 0–2 km from the CBD, where urban parks provide only direct benefits, but forests provide only indirect benefits; the use of both would provide both types of capitalization benefits, which is an interesting dimension in spatial economic planning.

## 7. Conclusions

This study has employed spatial hedonic specifications to assess two spatial aspects in the marginal effects of distance to forests, parks, and fields on apartment prices: the interaction of the estimated effect with a distance to the city centre gradient; and the spatial diffusion character of those effects along the same gradient.

The estimations indicate that the three different green types yield different marginal effects and these depend on location within the city and the nature of spatial spillovers generated. While it is fair to say that decreasing distance to all three green types has the potential to increase price/$m^2$, the realisation of this potential into actual benefits depends on refining the type of spatial impact and the location along the distance to the CBD gradient. Additionally, there are a few distinct zones along this gradient where the marginal effects of different green types overlap. These may be taken as a cautious indication of substitutability—with the discussed valuation literature in Section 5 supporting such interpretation—but it can more conservatively be taken to represent complementarity, as one type of urban green can cover for particular impacts that another type cannot provide at a certain location along the CBD gradient.

Obviously, the interpretation of pure versus spillover effects is central in this argument and the topic is not sufficiently developed in the hedonic context. In this study, it is proposed that the separation of pure from spillover impacts makes sense if one considers who pays versus who receives the benefits of a change in the distance to a certain green type; as seen above, the extent to which benefits diffuse in a spatially dependent market varies per green type and per location along the CBD gradient. Alternatively, one may elect to focus on where the change happens, rather than who invests. In this case indirect impacts become particularly important, because changes in the distance to green of neighbouring properties may affect the price of a given property without the property itself having experienced (or invested in) such a change.

Table 5 presents in a schematic manner this parameterization of benefits per location, type of green, and type of spatial intervention. The primary utility of this table is to illustrate that climate adaptation or other urban strategies that rely significantly on urban green ought to move towards a more detailed conceptualization of urban green and the price effects it may represent.

Although the results as such represent the marginal contribution of distance from green patches to housing prices, it should be noted that in planning practice such analysis refers to plannable green solutions

**Table 4**
Spatial impacts simulation results, full sample.

| Coef. & signif. | | | | | | |
|---|---|---|---|---|---|---|
| | FOREST | FOREST * CBD | PARK | PARK * CBD | FIELD | FIELD * CBD |
| Direct | 0.464*** | −0.053· | −0.046*** | 0.015*** | 0.164*** | −0.062*** |
| Indirect | −1.110*** | 0.261*** | −0.680*** | 0.066*** | 0.064*** | 0.032*** |
| Total | −0.646** | 0.208*** | −0.725*** | 0.081*** | 0.228*** | −0.030*** |

Notes:
1. Significance ranges: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.
2. Simulated significances are based on $R = 1000$ replications.

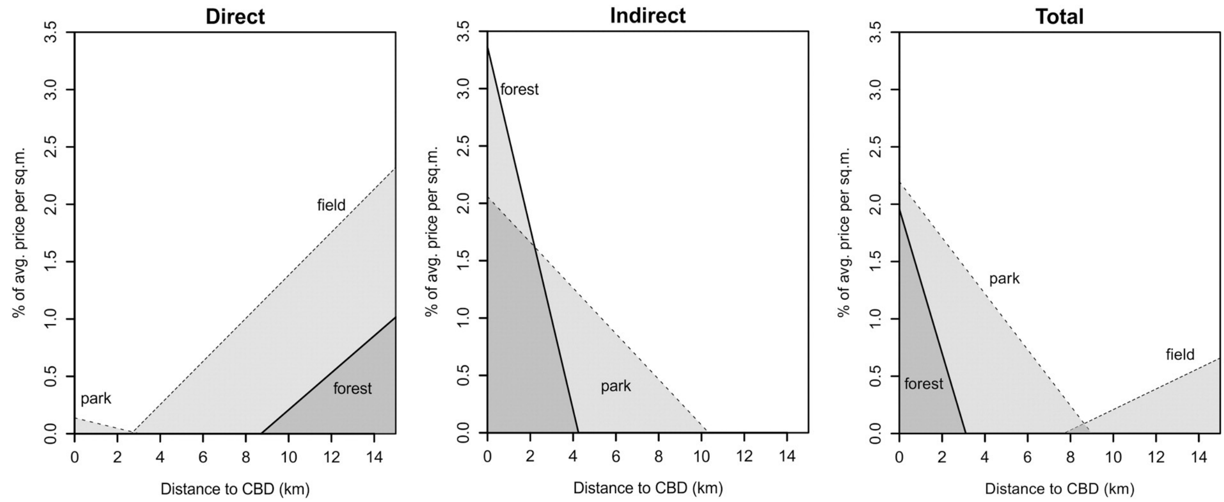


**Fig. 4.** Direct (left), indirect (middle), and total (right) spatial impacts of forests, parks, and fields.

or investment options. The results can thus contribute to the topic of implementing green infrastructure in a systematic or comprehensive manner (cf. the strains of strategic and comprehensive planning). Hedonic results, although partial, provide empirical guidance that identifies less-than-optimal implementations that may hinder other functions of the urban economy, and also indicate solutions that are likely to better harmonize green interventions with a broader array of socio-economic objectives.

The effects of the quantity of green and/or the spatial arrangement of a fixed quantity have not been treated in this study, largely due to the limitation of regression analysis to answer these questions. The main reason for caution against extending the results into such discussions (for instance, do we allocate 1 ha of green into a few large parks, or into several smaller patches) is that the ceteris paribus assumption can be rapidly violated in this context: changing one parameter will in fact cause a change in most other factors, due to the dynamical nature of the system and the scarcity of available land. Nevertheless, while not a complete spatialized account of a city's economy and activities, this analysis confirms that cities are not monolithic organisms (cf. Batty, 2007) and different locations have different economically optimal green solutions, with the empirical information helping towards a more systematic planning of green infrastructure.

The study also explored to some extent the problems stemming from the treatment of temporally aggregate data and from the mixing of pure and spatial spillover effects. The approaches of estimating models in temporal subsets and the approach of separating pure from spatial spillover effects appear to provide clearer and more sensible intuitions; both model alternatives indicate that a large pooled model may have technical merits, but also has the risk of incorrectly estimating coefficients for urban green, or failing to detect significant results altogether. In the case of this study, this was an issue for estimating the marginal effect of distance to a forest; the pooled model is a clear misrepresentation in this respect, even though it estimated the effects of other environmental amenities correctly.

In conclusion, from the viewpoint of sustainable development's original concept of integration, the greening of cities appears to be far from an unconditional goal. Successful spatial solutions must be parameterised according to a few goals: to defining what the location in question is, what green types are considered, and what the intended extent of benefits is. Adding this detail is necessary because, as this study shows, some solutions have surprisingly unintended effects if conceptualized and implemented in the wrong way and wrong location.

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**Table 5**
Overview of the estimated effects of decreasing distance to urban green.

| *Effect* | *Type of green*<br>FOREST | PARK | FIELD | EFFECT OVERLAPS |
|---|---|---|---|---|
| Direct | ●●<br>▪ Max. in urban fringe | ●<br>▪ Max. in the CBD | ●●●<br>▪ Max. in urban fringe | ▪ >9 km: forest, field |
| Indirect | ●●●<br>▪ Max. in the CBD | ●●●<br>▪ Max. in the CBD | | ▪ 0–4 km: park, forest |
| Total | ●●●<br>▪ Max. in the CBD | ●●●<br>▪ Max. in the CBD | ●●<br>▪ Max. in urban fringe | ▪ 0–3 km: forest, park |

Notes:
● 0–1% $m^{-2}$; ●● 1–2% $m^{-2}$; ●●● 2–3.5% $m^{-2}$, referring to the price effect of a 100 m change of distance to a green patch.
All kilometre (km) figures refer to distance from the central business district (CBD) of Helsinki, defined as the point of densest commercial establishments within the broader metropolitan region.

## Appendix A. Regression estimations

**Table A-1**
[Spatial error estimation results, biannual samples].

| Coef. (std. error) | | | | | | |
|---|---|---|---|---|---|---|
| | 2010–11 | 2008–09 | 2006–07 | 2004–05 | 2002–03 | 2000–01 |
| INTERCEPT | 4.919*** | 5.266*** | 5.166*** | 4.647*** | 4.016*** | 3.725*** |
| | (*0.094*) | (*0.106*) | (*0.112*) | (*0.107*) | (*0.102*) | (*0.098*) |
| DEBT/m$^2$ | −0.565*** | −0.604*** | −0.541*** | −0.639*** | −0.614*** | 0.476*** |
| | (*0.014*) | (*0.016*) | (*0.019*) | (*0.034*) | (*0.039*) | (*0.039*) |
| COST/m$^2$ | −0.019** | −0.018* | −0.021** | −0.031*** | 0.004 | −0.028*** |
| | (*0.007*) | (*0.007*) | (*0.008*) | (*0.005*) | (*0.003*) | (*0.004*) |
| ROOMS | −0.254*** | −0.181*** | −0.148*** | −0.113*** | −0.133*** | −0.064*** |
| | (*0.006*) | (*0.006*) | (*0.006*) | (*0.006*) | (*0.007*) | (*0.006*) |
| AGE | −0.025*** | −0.024*** | −0.020*** | −0.019*** | −0.016*** | −0.011*** |
| | (*0.001*) | (*0.001*) | (*0.001*) | (*0.001*) | (*0.002*) | (*0.002*) |
| [AGE]$^2$ | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (*0.000*) | (*0.000*) | (*0.000*) | (*0.000*) | (*0.000*) | (*0.000*) |
| FLOOR | 0.071*** | 0.070*** | 0.076*** | 0.050*** | 0.040*** | 0.049*** |
| | (*0.003*) | (*0.004*) | (*0.003*) | (*0.004*) | (*0.004*) | (*0.004*) |
| BADCOND | −0.518*** | −0.596*** | −0.491*** | −0.382*** | −0.364*** | −0.168*** |
| | (*0.028*) | (*0.028*) | (*0.026*) | (*0.030*) | (*0.033*) | (*0.018*) |
| (AVGCOND | −0.249*** | −0.251*** | −0.273*** | −0.218*** | −0.141*** | −0.138*** |
| | (*0.012*) | (*0.013*) | (*0.012*) | (*0.013*) | (*0.015*) | (*0.014*) |
| CBD | −0.120*** | −0.270*** | −0.269*** | −0.221*** | −0.173*** | −0.191*** |
| | (*0.011*) | (*0.017*) | (*0.019*) | (*0.017*) | (*0.015*) | (*0.016*) |
| LOTSIZE | 0.000· | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (*0.000*) | (*0.000*) | (*0.000*) | (*0.000*) | (*0.000*) | (*0.000*) |
| RLINE | 0.110*** | 0.194*** | 0.158*** | 0.100*** | 0.088*** | 0.114*** |
| | (*0.017*) | (*0.028*) | (*0.030*) | (*0.028*) | (*0.025*) | (*0.025*) |
| MLINE | 0.088*** | 0.087*** | 0.078*** | 0.075*** | 0.078*** | 0.085*** |
| | (*0.008*) | (*0.012*) | (*0.012*) | (*0.012*) | (*0.011*) | (*0.011*) |
| MJROAD | 0.101*** | 0.154*** | 0.180*** | 0.107** | 0.026 | 0.040 |
| | (*0.028*) | (*0.037*) | (*0.039*) | (*0.038*) | (*0.035*) | (*0.038*) |
| COAST | −0.144*** | −0.003 | −0.035 | −0.040 | −0.057* | 0.000 |
| | (*0.017*) | (*0.029*) | (*0.030*) | (*0.029*) | (*0.026*) | (*0.026*) |
| FOREST | −1.097*** | −0.269 | −1.374*** | −1.359*** | −0.764* | −1.169*** |
| | (*0.215*) | (*0.360*) | (*0.349*) | (*0.316*) | (*0.339*) | (*0.330*) |
| FOREST ∗ CBD | 0.256*** | 0.042 | 0.198** | 0.0204*** | 0.115· | 0.186** |
| | (*0.044*) | (*0.066*) | (*0.062*) | (*0.056*) | (*0.060*) | (*0.063*) |
| PARK | −0.578*** | −0.769*** | −0.749*** | −0.552*** | −0.139 | −0.355* |
| | (*0.129*) | (*0.149*) | (*0.156*) | (*0.149*) | (*0.142*) | (*0.144*) |
| PARK ∗ CBD | 0.059*** | 0.093*** | 0.085*** | 0.065*** | 0.017 | 0.048** |
| | (*0.015*) | (*0.016*) | (*0.017*) | (*0.016*) | (*0.015*) | (*0.015*) |
| FIELD | 0.566*** | 0.150** | 0.138** | 0.057 | 0.050 | 0.025 |
| | (*0.030*) | (*0.046*) | (*0.048*) | (*0.044*) | (*0.042*) | (*0.041*) |
| FIELD ∗ CBD | −0.058*** | −0.027** | −0.027** | −0.016· | −0.012 | −0.020* |
| | (*0.006*) | (*0.009*) | (*0.009*) | (*0.009*) | (*0.008*) | (*0.008*) |
| YEAR | 0.049*** | 0.072*** | 0.163*** | 0.161*** | 0.110*** | −0.138*** |
| | (*0.011*) | (*0.012*) | (*0.010*) | (*0.011*) | (*0.013*) | (*0.013*) |
| N | 10,839 | 9532 | 9330 | 6513 | 4755 | 5013 |
| Pseudo $R^2$ | 0.8 | 0.7 | 0.7 | 0.78 | 0.7 | 0.67 |

Notes:
1. Significance ranges: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.
2. The unit of the ecological independent variables is distance to the green feature in kilometres.
3. The unit of the dependent variable is the property's selling price in € thousand per square meter.

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