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Methodological and Ideological Options

Exposure to green areas: Modelling health benefits in a context of study heterogeneity

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ABSTRACT

Although the beneficial health effects of green areas are gaining recognition, epidemiological studies show mixed results with significance varying considerably by study and context, indicating that there is no unique and clear evidence. This relationship is influenced by multiple factors and characterised by high complexity not previously been incorporated in one single analysis. This study proposes a new application of the Heckman selection model to find evidence of key patterns emerging throughout the literature and identify main determinants affecting the relationship. The model aggregates outcomes of different studies and allows an assessment of both significant and non-significant results from the literature in order to correct for unobserved selection bias. Close attention is paid to the relevance of the background, particularly socioeconomic context. The results show significant health benefits associated with increased exposure to green areas, where higher risk reductions are observed for old and adult age groups, as well as in poorer countries, taking into account the correction for the publication bias. This last issue points towards a redistributive impact of green areas in terms of health and the importance of co-benefits arising from Ecosystem-based Adaptation, especially in poorer neighbourhoods, translating in health care savings and reduced productivity loss.

1. Introduction and background

One of the trends constantly present during most of recorded history has been the increase in the population living in cities. Urbanization is a process that has also accompanied industrialization all over the world. In such context, lack of contact with the natural environment is a growing concern (Antrop, 2004; Chen et al., 2008; Wright Wendel, 2011; Wright Wendel et al., 2012). Nature has been identified as an important factor influencing human health. Among the potential benefits that nature offers to individuals, improved health may be put among the most important and a growing body of literature reflects this (Gascon et al., 2016; Lee and Maheswaran, 2010; Lovell et al., 2014).

The relationship between natural and semi-natural environments on the one hand, and human health and wellbeing on the other, has been considered not only by the scientific community but also by entities in charge of promoting health and protecting the environment. The World Health Organization (WHO) accounts for various environmental aspects among the main determinants of health (World Health Organization, 1986). The interactions between environment and health are complex. Environmental factors pose serious risks to human health, as it is estimated that 24% of the global burden of disease is attributable to environmental hazards (WHO, 2006), including air and water quality, land use and urban design. Contacts with healthy environments are therefore central for promoting a better health in the population. This is even more important in the current trend characterised by an increase of non-communicable diseases (NCDs) (e.g. cardiovascular and respiratory diseases, diabetes, cancer) which, according to the WHO, will generate a cost of > 11 billion US$ to the world economy during the 2011–2025 period (Mendis, 2014). Projections indicate a rise from 36 million deaths due to NCDs in 2008 to 44 million by 2020 globally, especially in urban areas and among poorer groups (WHO, 2011). Prevention of these diseases can be achieved through improved accessibility to healthy environments and promotion of healthier lifestyles (e.g. physical outdoor activity, recreational activities in rural areas and green spaces, etc.). Green areas can play a key role in this context, while providing also other benefits such as reducing health inequalities, improving urban biodiversity and contributing to adaptation to climate change (Chiabai et al., 2018).

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Different approaches have been taken in order to explain the interactions environment-human health and the associated benefits (Martinez-Juarez et al., 2015). For example, trees can help mitigate risks from air pollution by retaining contaminants present in the urban atmosphere (Nowak et al., 2006), both chemical and acoustic (Stansfeld and Matheson, 2003). Exposure to green environments also interacts with the human microbiome, which can lead to effects on the incidence of inflammatory diseases such as allergies (Rook, 2013; Rook et al., 2013). Among other things, green areas can reduce surface runoff, hence contributing to reduced risks derived from flooding in urban areas. Water cycle regulation provided by wetlands and other ecosystems have important impacts on water supply and water quality. Socioeconomic determinants have also been considered by some authors among the factors mediating in the relation between environment and health. Parks and other open green spaces may promote social cohesion by providing meeting and leisure areas, which may have positive impacts over mental health. The implications for social and economic welfare go beyond this mediating effect. The health burden is particularly strong for income deprived populations. Vulnerable populations are more prone to poor health, and this relationship extends to various aspects of health (Aschan-Leygonie et al., 2013; Mendis, 2014; Mitchell and Popham, 2008; Roe et al., 2013; Ward Thompson et al., 2014, 2012). Health inequalities may lead to poverty traps (Whitehead et al., 2001), with worse health conditions often being accompanied by low incomes. Worse eating habits, lower accessibility to health care, stress and many other causes may lay behind this situation, but improved access to green areas is among the possible mechanisms that have been proposed to reduce this aggravated impacts (Ward Thompson et al., 2014). Urban green areas provide public open spaces that help vulnerable segments of society to access to active leisure or benefit of cleaner air, as well as to improve social links. This may lead to a potential higher health improvement in deprived populations, hence contributing to health inequalities and the associated poverty trap (Mitchell and Popham, 2008). Socio-economic factors can therefore be seen as contextual variables contributing through different pathways to the expected health benefits of improved environments.

In this context, making a comprehensive review of the existing literature is a complicated task. This is due to various reasons. The first is the fact that number of studies relating exposure to natural and semi-natural environments and heath is still growing. Due to critical importance of the issue, this field has attracted many investigators from different backgrounds. This leads to the second challenge, the heterogeneity of methodologies and underlying assumptions. Methodological heterogeneity occurs at different points of the research, such as the variable measurement (e.g. health effect, exposure), the population selection, the inclusion of contextual factors, and the analytical tools employed. Issues of comparability among studies and the use of different measures of health and green space complicate the identification of the underlying dose-response relationships. This leads to uncertainty as to the “true” relationship between green spaces and health. While there is a seemingly positive relation explored along the literature, the presence of non-significant and negative correlations has led some authors into questioning the validity of any generalization (Lee and Maheswaran, 2010).

Against this background, we aim to explore new approaches to deal with the existing study heterogeneity, in order to extract generalizable conclusions from the literature linking green spaces and human health (Martinez-Juarez et al., 2015). This is a crucial step to facilitate knowledge transfer from academics to civil society on the importance of green space. The hope is that it will also inform better interdisciplinary research in a field where various disciplines may interact.

More specifically, the objective of this paper is to explore the potential use of the Heckman selection model, as a way of identifying the factors influencing the significance of the relationship throughout existing studies and calculating the marginal effects of selected factors found to be crucial. A literature review has been conducted for this purpose, including studies with quantitative results on the health benefits (in terms of risk reductions) associated with increased availability of green areas, and a database has been constructed with all relevant variables believed to influence this relationship.

The paper is organized as follows. Section 2 presents the methodological approach, including the process of constructing the database with data obtained from the literature and external sources (Section 2.1), the definition of the variables and standardization process (Section 2.2), the Heckman selection model and its application to the current study (Section 2.3), and the marginal effects associated (Section 2.4). Results are shown in Section 3, starting with the descriptive statistics (Section 3.1) and following with the results of the analysis (Section 3.2), while Section 4 presents a discussion of these results and the key conclusions.

2. Methods

2.1. Selection of previous case studies and database

A literature review was conducted including peer reviewed publications on the health benefits provided by green spaces, using a worldwide geographical coverage. This searching process included a systematic search through a set of selected keywords related to natural environment and health which was described by Chiabai et al. (2018). A detailed analysis of the outcomes and approaches was also conducted in order to incorporate the information into a common dataset which was used afterwards for the econometric analysis. Chiabai et al. (submitted DiB) describes the steps taken from the literature review to the construction of a quantitative database summarising the main results extracted and used for the present analysis. As described in this last paper, the dataset included studies offering quantitative results linking green areas and human health. Table 1 reports the studies included in the database in terms study location, methods, type of health outcomes, health and green exposure indicators, number of observations available in each study as well as those with significant results in the undertaken analysis. It must be highlighted that the reviewed studies use availability of green areas as a measure of exposure as it is discussed later in this section.

The observations reported in Table 1 are those extracted from each study to build the Heckman model and carry out the statistical analysis as specified in the next sections. Each observation is recorded in terms of a specific health indicator which measures the change in the health outcome due to increased availability of green areas, as indicated in Table 1 and discussed more specifically in Section 2.2. For example, in Maas et al. (2009), the observations are in terms of changes in annual prevalence rate (health indicator) in different diseases (health outcome), associated to an increase in green spaces availability near the respondents' residence. The health outcomes in Table 1 refer to the specific effects on health, such as mortality, disease occurrence, perceived health, as discussed in detail in Section 2.2.

The literature was found to be quite diverse with respect to many aspects, notably the methodological approach, the definition and indicators used for the health outcome and for exposure, which leads to significant statistical heterogeneity. As shown in Table 1, results are mixed with significance varying considerably by study and type of health outcome, suggesting that there is no unique and clear evidence of the impact produced by green environment on human health. We briefly discuss hereby the main issues related to the diversity of the studies reviewed, and in a second step how the data from Table 1 have been standardized to construct a database for the econometric analysis (Sections 2.2 and 2.3).

The first point to highlight is the variety of methods and statistical techniques used in the literature to analyse the relationship health-green environment, depending on the type of data available, the purpose of the analysis and the health outcome analysed (for a discussion see Chiabai et al., 2018). The studies reviewed can be categorized in

Table 1
Studies included in the database.
Source: Chiabai et al. (submitted DiB).

Study	Location	Method	Health outcomes	Observations		Health indicator	Green exposure indicator
				Total	Significant effects		
Maas et al., 2009	Netherlands	Multilevel logistic regression analyses	24 outcomes[a]	58	26 (44.8%)	Annual prevalence rate	Percentage of green space in a radius of 1 and 3 km around the postal code of respondent's home
Maas et al., 2006	Netherlands	Multilevel logistic regression analyses	Perceived general health	6	6 (100%)	Percent of responses (5-point Likert scale – very poor to very good)	Percentage of green space in a radius of 1 and 3 km around the postal code of respondent's home
Takano et al., 2002	Tokyo, Japan	Multiple logistic regression analysis	All-cause mortality	21	8 (38.1%)	Five-year survival rate for the elderly	Presence of walkable green spaces near the residence (parks and tree lined streets) measured with qualitative indicators
Mitchell and Popham, 2008	England	Binomial regression model	All-cause mortality, circulatory diseases and cancer	15	9 (60%)	Mortality incidence rate	Population classified into 5 exposure groups based on the proportion of green space of residence
Pereira et al., 2012	Perth, Australia	Logistic regression	Coronary heart disease	4	1 (25%)	Hospital admissions and self-reported medically diagnosed cases	Neighbourhood greenness for a 1600 m service area around residence using remote sensing data
White et al., 2013	England	Fixed effect regression	Perceived general and mental health	12	10 (83.3%)	Percent of responses (5-point Likert scale – poor to excellent)	Distance to the coast (0–5 km; 5–50 km; > 50 km) and percentage of green space
Dunstan et al., 2013	South Wales	Multilevel logistic regression model.	Perceived general health	3	2 (66.7%)	Percent of responses (3-point Likert scale – not good-fairly good-good)	Neighbour measure of natural environment through Residential Environment Assessment Tool (REAT)
Tamosiunas et al., 2014	Kaunas, Lithuania	Multivariate Cox proportional hazards regression	Cardiovascular disease, fatal and non-fatal	21	0 (0%)	Age-adjusted prevalence (%)	Distance to city parks larger than 1 ha, categories classified based on spatial land cover data
Pretty et al., 2005	Colchester, UK	One-way ANOVA test	Perceived mental health (depression and anxiety)	4	3 (75%)	Percent of responses (5-point Likert scale –not at all to extremely)	Exposure to visual stimuli (rural and urban photographic scenes)
Marselle et al., 2013	England, UK	One-way ANOVA test	Perceived stress and depression	14	2(15%)	Use of Major Depressive Inventory and a 10-item Perceived Stress Scale	Questionnaire on participants' walking environments
Roe et al., 2013	Dundee, UK	Multiple linear regression	Perceived mental health (stress)	4	2 (50%)	Perceived stress score (5-point Likert scale –never to very often)	Percentage of green space (parks, woodlands, scrub and other)
Kerr et al., 2006	Japan	Doubly multivariate profile analysis (MANOVA)	Anxiety	2	1 (50%)	Tension and Effort Stress Inventory	Outdoor running session vs- outdoor running in natural environment

[a] Cardiovascular, respiratory, musculoskeletal, digestive, mental, neurological, miscellaneous.

Table 2
Description of variables.
Source: Chiabai et al. (submitted DiB).

Variable	Description	Data source	Units
Health risk reduction	% change in the health indicator due to an increase in exposure respect to a baseline defined as low exposure.	Reviewed studies	% change
Exposure to green areas	Availability of green spaces in the surroundings of people's living environment, measured in terms of vicinity and/or % or density of green.	Reviewed studies	Categorical variable (1 for low exposure, 2 for medium exposure and 3 for high exposure)
Mortality	Mortality versus morbidity impact. It allows measuring the differential effect between mortality and morbidity.	Reviewed studies	Dummy variable (1 for mortality, 0 morbidity)
Disease type	General (all-cause, general health), mental, cardiovascular, respiratory, others (diabetes, cancer, etc.).	Reviewed studies	Categorical variable
Female	Proportion of female population over the total.	Reviewed studies	Percentage (of female on total)
Age	Age groups: young < 16, adults 16 to 65, elderly > 65.	Reviewed studies	Percentage (of population in each age group)
Subjective	If the study relies on self-reported health, the observation is regarded as subjective, otherwise not.	Reviewed studies	Dummy variable (1 for the subjective studies, 0 otherwise)
Income per capita	GDP/population by country.	Secondary source: IMF (http://www.imf.org/external/pubs/ft/weo)	GDP per capita
Hospital beds	Hospital bed density (by country).	Secondary source: CIA library (https://www.cia.gov/library/publications)	Number hospital beds per 1000 people
Literacy	Literacy rate, youth total (% of people ages 15–24, by country).	Secondary source: World Bank (http://data.worldbank.org/indicator)	Percentage
Urbanization	% people living in urban areas (as defined by countries' statistical agency)	Secondary source: World Bank (http://data.worldbank.org/indicator)	Percentage

two main groups, "objective" and "subjective" studies. The first use health indicators computed with objective measures drawn from health registries (mortality rate, prevalence/incidence of specific diseases, hospitalization rate, life expectancy). The second rely on subjective measures such as opinions and individual perceptions on health status, quantified in survey-based questionnaires with qualitative measures using the Likert scale technique (e.g. "very poor" to "very good"). Both types of measures were used in the econometric analysis based on the recognition that they are equally important in defining the relationship between exposure and individual health status. There is some evidence that self-reported, subjective measures of health may underreport the prevalence of certain conditions, including cardiovascular diseases, and that such measures may mask socioeconomic gradients in disease risk (Mosca et al., 2013). Controlling for the impact of the type of health measures used is hence important.

Defining exposure to green areas is another major issue when it comes to analysing their effects on health. The studies in the literature review generally refer to *increased availability* of green spaces within a certain distance from people's living environment and use different metrics for this purpose (e.g. spatial land cover data, Normalized Differences Vegetation Index – NDVI). Accessibility, usability and quality of the green space, on the other side, are associated with a number of factors such as promotional activities, provision of footpaths and exercise facilities, appropriate lighting, enhanced aesthetics and mixed land-use, good air quality, while it can be hindered by factors such as low path connectivity, heavy traffic and contamination. There are not many studies in literature with quantitative analysis in regard to the wider quality and accessibility metrics which could be used in our modelling exercise Greenspace is heterogeneous in nature, and though studies are starting to consider these factors (e.g. Wheeler et al., 2015), they are as yet few in number. As a result, these factors have not been contemplated in our analysis. We consider "*increased availability*" of green spaces and use it as a proxy of "exposure" as referred in the reviewed literature. Future research might build on the basic model developed in the current analysis to include more complex analysis based on more refined indicators reflecting exposure.

2.2. Variables in the model and standardization process

The two main variables to include in the model are the health benefits (dependent variable) and the increased exposure to green areas (as explanatory variable). Given the diversity of indicators used for these two variables, some assumptions for standardization are needed to carry out the analysis under a common measurement framework. Our first order of business was therefore to create standardized indicators for a common measure allowing for comparison among the results.

The health indicator in each study measures the change in the health effects due to an increase in exposure to green areas. In the reviewed studies, the health indicator may refer to objective indexes, such as mortality incidence rate, five years' survival rate, life expectancy, annual prevalence/incidence of diseases, hospital admissions, measured from estimated coefficients in epidemiological functions. Alternatively, it may also refer to subjective indexes, such as the general health perception measured on a Likert scale. All these indexes taken from the different studies, once collected, were transformed into a *standardized percent variation rate* referring to different health outcomes, which defines our standardized indicator "health risk reduction" (HRR).

As regards the explanatory variable of exposure to green areas, the indicators used in the reviewed studies may refer to the distance of the respondents' home to the nearest park, or percentage of green spaces in the surroundings of respondents' living environment, or normalized difference vegetation index (NDVI) in the living environment which identifies if a target space contains green vegetation or not. In order to create a common standardized indicator for exposure, we constructed a qualitative variable taking three values for exposure: low, medium and high. For each study, we created three intervals based on the cumulative distribution function of the specific indicator of exposure used in the corresponding analysis (size or distance from the homes of participants). In each study, the lowest level of exposure is taken as the baseline, the second tercile is taken as a medium exposure level, while the third tercile group represented a high exposure. The baseline acts as reference, and refers to those groups of individuals who are less exposed, if at all, to green areas. Further detail is given in Chiabai et al. (submitted DiB).

The full set of variables included in the database (Supplementary data) is presented in Table 2 and detailed in Chiabai et al. (submitted DiB). The rationale behind the selected explanatory variables rest on their use in the two equations of the Heckman model (Section 2.3). A first set of explanatory variables are assumed to be affecting the health risk reduction in the *outcome equation* (see Section 2.3), and these include increased exposure, mortality, disease cluster, a dummy variable to reflect whether the study used subjective measures or not, age, a dummy variable for gender, income per capita and hospital beds density.

In order to differentiate the health impacts, the following variables were constructed, discriminating among (a) mortality versus morbidity effects (dummy "mortality"), (b) objective versus subjective studies (dummy "subjective"), and (c) type of illness (categorical variable "disease type"). Five dummies were derived from the categorical variable: mental health, cardiovascular diseases, respiratory diseases, other health impacts not included in previous categories (e.g. musculoskeletal, neurological, digestive, diabetes, cancer), and a universal category "general" (all-cause and general health). The latter is used in the literature as a comprehensive classification to refer the general individual health status.

The variable "subjective" is related to the differentiation between indicators used in "objective" and "subjective" studies respectively, which might affect in a different way the relationship health-exposure. The same applies for the "mortality" and "disease type". For example, we are interested in investigating possible differences in impacts among the groups of illnesses, and between mortality and morbidity. We also include a number of demographic and socio-economic variables as control factors. Some of them were available in the studies reviewed in the database ("female" and "age"), while others were taken from secondary sources, such as "hospital beds density" and "income per capita" at the country level. Hospital beds density (defined as the number of hospital beds per 1000 people) represents a proxy for the access to the health care system, under the assumptions that higher access to health care services would guarantee better population health status. The variable "income per capita" is assumed to negatively affect the health risk reduction, in line with previous studies in the literature according to which poorer groups are benefitting more from exposure to green areas.

A second set of explanatory variables, some of the them in common with the first set, are capturing the *i-Study Effect* in the *selection equation* (see Section 2.3) designating:

- Socio-economic aspects on the country where the study was done, captured by "income per capita", "urbanization", "literacy" at the country level, taken from secondary sources. "Urbanization" refers to the percentage of people living in urban areas and reflects a proxy for urban lifestyle. "Literacy" refers to the percentage of people literate aged 15–24 and reflects the effect of knowledge.
- Characteristics of the study, captured by "subjective" (meaning subjective versus objective nature of the study) and "mortality" (meaning that the study focus on mortality versus morbidity outcomes), taken from the reviewed studies.

We assume that these variables can affect the significance of the results obtained in the reviewed studies. Some of these variables are in both equations, as they capture both the effect on the health risk reduction as well as the *i-Study Effect*. This is the case of "income per capita", "subjective" and "mortality". Their interpretation in light of the results obtained is discussed in Section 3.

2.3. The Heckman model

Though most of the studies reviewed support the idea that green areas can have beneficial effects on human health, this relationship is influenced by multiple factors (environmental, socio-demographic and economic) and is therefore characterised by high levels of complexity and uncertainty. Indeed, many of the studies found in the review, show non-significant results. This implies unclear evidence for health benefits from green areas at the current stage. In such cases, considering only the studies providing significant results would generate a censored sample which would lead to inconsistent and biased parameter estimates (Copas, 2013). At the same time, the presence of more than one estimated coefficient reported per study would give an excess weight to studies with many estimates (Stanley, 2001).

Previous studies introduced a dummy variable for each study that provided more than one observation for the meta-analysis (Jarrell and Stanley, 1990). Other solutions (Jeppesen et al., 2002) try to derive estimates from meta-analyses combining a probit model and an unbalanced panel data model to take into account the random researcher effect and to assess the impact due to the commonality within a study and assuming that reporting a significant result in a study is separate from the amount observed. Further studies (Rolfe and Brouwer, 2012), used a mixed-effects Tobit model to take into account the censored nature of the data and the intra-study effects, assuming structural similarity restrictions on coefficients for censored and non-censored observations. One way to take into account some of the limitations mentioned, would be to estimate with panel data a model selection (Wooldridge, 1995; Semikyna and Wooldridge, 2010), but this procedure would not be feasible due to the nature of our data, as it presents neither the proper rationale (we could not compare the observations among the different papers), nor enough degrees of freedom to adequately select the cohorts for the pseudo-panel needed to estimate the j-Probit models in the first step, as proposed in those articles. Therefore, in this context of uncertainty, we tested the Heckman selection model as a way to deal with the unobserved selection factors and correct for the bias in estimating the outcome equation, and we introduced variables related with the study to control for the researcher effect. In our analysis, we name this effect as the i-Study Effect, as it is explained in the next sections.

Our objective is to gather the quantitative results available in the literature about the relationship health and green areas in a meta-analysis in order to model quantitative impacts on health associated with exposure to green areas in a context of study heterogeneity.

The Heckman selection model is usually expressed in terms of latent variable models and relies on two equations, an *outcome equation* which includes factors affecting the outcome variable, and a *selection equation* which considers the part of the sample which is observed and the factors influencing the selection process.

In our case, the *outcome equation* relates the health risk reduction with a set of explanatory variables such as increased exposure level, income per capita, type of disease and so on.

In its general form, the outcome equation R_i can be expressed as:

$$R_i = X_i\beta + \varepsilon_i \tag{1}$$

where X_i are the explanatory variables determining the health risk reduction R_i; β is a vector of parameters to be estimated; andε_i is the error term. In our analysis Eq. (1) takes the following form:

$$\begin{aligned} R_i &= \beta_0 + \beta_1 mort_i + \beta_2 sub_i + \beta_3 car_i + \beta_4 res_i + \beta_5 men_i + \beta_6 gen_i + \beta_7 \\ &\quad exp_{m,i} + \beta_8 exp_{h,i} + \beta_9 fem_i + \beta_{10} old_i + \beta_{11} adult_i + \beta_{12} logGDP_i + \beta_{13} \\ &\quad \log bed_i + \varepsilon_i \end{aligned} \tag{2}$$

The explanatory variables are those reported in Table 2, though some of them have been further transformed in dummies, as specified hereby. $mort_i$ is the dummy variable "mortality" when mortality is measured in study *i*. sub_i is the dummy variable "subjective" indicating if the observation is a subjective health perception derived from surveys. The four variables car_i, $resp_i$, men_i, gen_i are dummies derived from the categorical variable "disease type" in Table 2, and they are interpreted in comparison with the category "others" (diabetes, cancer, etc.). car_i, is the dummy variable for cardiovascular diseases, res_i for respiratory diseases, men_i for mental health and neurologic diseases, and gen_i for other diseases (digestive, muscular, etc.).Exposure is measured with two dummies, exp_m and exp_h, derived from the categorical variable

Table 3
Descriptive statistics of principal variables.

Variable	Whole sample (all observations)		Subsample (significant results only)	
	Mean	Std. dev	Mean	Std. dev
Health risk reduction	0.848	1.799	1.755	2.263
Mortality	0.297	0.458	0.398	0.492
Subjective	0.247	0.433	0.295	0.495
Exposure to green areas				
● High	0.297	0.458	0.34	0.477
● Medium	0.445	0.498	0.307	0.464
● Low	0.26		0.35	
Disease type				
● Cardiovascular	0.220	0.415	0.08	0.272
● Respiratory	0.044	0.206	0.045	0.209
● Mental	0.198	0.399	0.216	0.414
● General	0.324	0.469	0.477	0.502
● Others	0.214	0.411	0.182	0.388
Urbanization	81.128	6.458	82.447	4.103
Hospital beds	6.131	3.993	5.476	3.79
Age				
● Young < 16	14.285	7.854	14.28	8.638
● Adults 16–65	59.724	26.489	60.72	27.511
● Elderly > 65	25.991	31.236	25.0	31.731
Female	51.966	17.226	48.673	14.448
Literacy	99.139	0.259	99.05	0.154
Income per capita	29,842.61	10,815.74	30,994.29	8190.77

Note: number of observations = 182.

"exposure to green areas" in Table 2 and representing medium and high respectively compared with low exposure. fem_i is the proportion of females in each observation. old_i and $adult_i$ denote the proportion of population over 65 and between 16 and 65 respectively, taken from the variable "age" in Table 2. *GDP* is the "income per capita" expressed in 2005 USD. bed_i is the number of "hospital beds" in the country per 1000 inhabitants.

The *selection* equation is the probability that the health risk reduction due to exposure is significant (probability of significance being observed, S_i), which can be expressed as:

$$S_i^* = Z_i\alpha + v_i \tag{3}$$

where Z_i are the explanatory variables assumed to capture the *i-Study Effect*; α is a vector of parameters to be estimated; and v_i is the error term. Eq. (1) is observed if $S_i = 1$, meaning that S_i^* shows significant effects on risk reduction from exposure, and $S_i = 0$ otherwise.

In our analysis the *selection* equation takes the following form:

$$S_i^* = \alpha_0 + \alpha_1 mort_i + \alpha_2 sub_i + \alpha_3 urb_i + \alpha_4 \log GDP_i + \alpha_5 lit_i + v_i \tag{4}$$

where urb_i is the variable "urbanization" (percentage people living in urban areas, per country) and lit_i is the percentage of literate people aged 15–24 in the country.

This is the latent variable model. If S_i^* shows significant effects of exposure on risk reduction then the observed latent function equals to 1, otherwise $R_i = 0$. The regression equation observes the value of R_i if $S_i = 1$. ε_i and v_i are the error terms of the two equations which are distributed according to a bivariate normal with mean zero, $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$, $v_i \sim N(0,1)$ and covariance $\rho = Corr(\varepsilon_i, v_i)$. The error terms are independent of both sets of explanatory variables. The model allows for correlation between unobservable information of the two equations. As it is well known, if $\rho = 0$, the standard regression model applied to Eq. (1) provides consistent and asymptotically efficient estimators for all model parameters. When $\rho \neq 0$, the standard regression model applied to Eq. (1) provides biased results, while the Heckman model with sample selection provides consistent and asymptotically efficient estimators for all model parameters.

The application of Heckman model in our context allows differentiating among those factors affecting the significance of exposure on the health risk reduction and to identify the key variables in this relationship.

2.4. Marginal effects within the Heckman model

To estimate the model coefficients, we used the full information maximum likelihood estimation method. The estimation involves forming the joint distribution of the two random variables [ε_i, v_i] and then maximizing the full log-likelihood function. The marginal risk reduction induced by the model determinants was then calculated on the basis of the estimated model considering the non-linear effects and for the mean values in the quantitative variables and the median values in the dummy variables.

The interpretation of the results from the model requires the transformation of the coefficients obtained in order to avoid selectivity bias. Vance (Vance, 2009) proposes marginal effects and significance testing following the equation:

$$\frac{\partial E(R_i \mid S_i^* > 0, X)}{\partial X_{ki}} = \beta_k - \alpha_k \rho \sigma_\varepsilon \delta_i(-Z\alpha) \tag{5}$$

where the inverse of the Mills ratio is denoted as $\delta(-Z\alpha)$, and it is to control for potential bias emerging from sample selectivity and it is calculated from the linear predictions $(-Z\alpha)$ of the selection equation. In general, the marginal effect of a variable X_k will be different for each observation (individual). As usual in such situations, we compute the value of the marginal effect for Z, a mean or median vector of variables (for quantitative or qualitative variables, respectively). The marginal effect estimated represents the variation in the health risk reduction (HRR) associated with a variation in the explicative variable once corrected for the selection bias.

3. Results of the model

3.1. Descriptive statistics

Table 3 shows the mean values and standard deviations of the created latent variable health risk reduction and its determinants. The first two columns refer to the whole sample of observations created from the results extracted from the literature review. Average values were taken for numeric variables and proportions in the case of dummy variables. The last two columns analyse the subsample created by selecting just those observations coming from significant results reported in the reviewed studies. The two variables HRR and increased exposure are measured with the standardized indicators as defined in Section 2.2. Overall, socioeconomic variables do not show great differences between the whole sample and the subsample. However, for HRR and exposure to green areas the difference between the two samples is higher which justifies the use of the Heckman selection model to take into account both significant and no significant results.

Fig. 1 shows how the relation between per capita income and health risk reduction is approximately flat when medium exposure is analysed while the slope becomes negative for a higher level of exposure. This relation has been built using the expected health risk reductions for each of the observations included database used for the analysis. This result implies that targeting the inequality through development of green spaces may require important developments in neighbourhoods in terms of green infrastructures in order to guarantee high exposure of citizens. The apparent trend linking higher income with lower potential for health improvements is nevertheless a relevant point. Higher potential for health improvements in lower income areas would imply an alleviation effect over health inequalities.

3.2. Estimate of a systematized function for health risk reduction as a response to green areas exposure

Table 4 shows the results of the Heckman Selection model

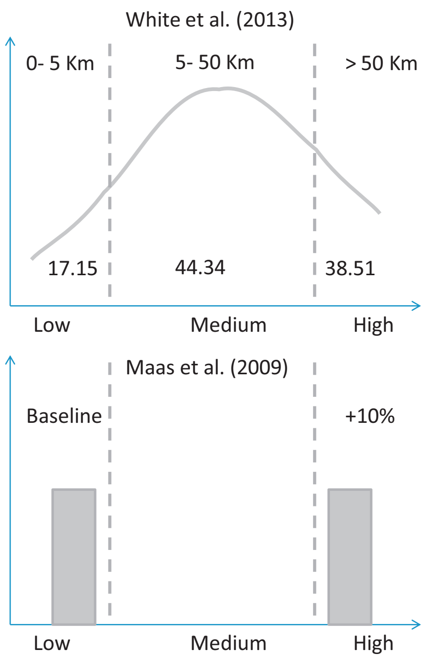

Fig. 1. Correlation between income per capita and health risk reduction for all-cause morbidity in the study sample. Marginal effects are calculated for mean values of quantitative variables and median values of the dummy variables of the sample. Note: number of observations = 182.

Table 4
Heckman Selection model results.

Explanatory variables	Outcome equation (R_i): HRR		Selection equation (S_i): probability that HRR significant	
Mortality *[mort]*	0.5716	(0.897)	1.7911	(0.435)***
Subjective *[sub]*	−0.0523	(0.849)	1.1635	(0.334)***
Cardiovascular *[car]*	−0.0875	(0.388)		
Respiratory *[res]*	−0.0309	(0.282)		
Mental health *[men]*	0.3941	(0.579)		
General health *[gen]*	−1.7318	(0.672)***		
Medium exposure *[exp_m]*	2.5682	(0.367)***		
High exposure *[exp_h]*	3.4530	(0.591)***		
Female *[fem]*	0.0051	(0.016)		
Elderly *[old]*	0.0593	(0.035)*		
Adults *[adult]*	0.0599	(0.038)*		
log income per capita *[log (GDP)]*	−2.1062	(1.310)*	−0.8408	(0.473)*
log hospital beds per capita *[log(bed)]*	2.6754	(0.715)***		
Urbanization *[urb]*			0.0793	(0.028)***
Literacy *[lit]*			−1.3205	(0.615)**
Constant	13.0054	(12.947)	132.1250	(62.209)**
Wald test of indep. eqns. (rho = 0): chi2(1) 3.27*				

Note 1: Figures are the estimated coefficients of the model and figures in brackets are standard errors.
Note 2: GDP and beds per capita have been transformed into log to consider the non-linearity effects.
Note 3: number of observations = 182.
* $p < .1$.
** $p < .05$.
*** $p < .01$.

separately for each equation. The *outcome* equation (R_i) explains the health risk reduction associated with exposure to green areas with a set of explanatory variables identifying different determinants. The *selection* equation, on the other hand, reveals the determinants affecting the probability of finding significant results in the risk reduction estimated in the reviewed studies. These determinants describe the *i-Study Effect* and include variables characterising the study and socio-economic factors in the country under analysis.

The results arising from the *selection* equation show that the probability of seeing significant results in the health risk reduction from increased exposure to green areas is significantly higher in studies conducted in urbanized countries, with lower income per capita and literacy rate, as well as in those studies looking at mortality outcome and subjective health indicators. The negative effect identified for income in determining the likelihood of a significant result may reflect the potential publication bias in the publication of negative results. Research in the medical sciences on clinical trials suggests that the odds ratio for the publication of significant results in higher income countries relative to other countries was 0.41 in 2003 (Yousefi-Nooraie et al., 2006), implying that studies in richer countries are more likely to report negative results.

As it can be seen in Table 4, the Wald test shows that the covariance between errors in the two equations is significantly different from zero, so that the two equations have to be jointly estimated. Also, we have tested the adequacy of our specification and our conclusions are: (i) we reject the null hypothesis of non-global significance of the outcome equation ($\chi^2(13) = 143.38$***), (ii) we reject the adequacy of the Tobit specification for the structural similarity restrictions on coefficients for censored and non-censored observations ($\chi^2(15) = 207.15$***) and (iii) we observe problems of collinearity if we introduce a dummy variable for each study.

In order to assess the magnitude of health risk reduction and its determinants, however, we need to look at Eq. (5) which estimates the marginal effects (Section 2.4) from the system of equations. In other words, in order to explain the results on the HRR we need to jointly estimate the outcome and selection equations, and interpret the resulting marginal effects in light of both equations. Eq. (5) measures the marginal values for the health risk reduction as a response to changes in the determinants—*dy/dx* for quantitative variables and discrete change of dummy variables from 0 to 1 (Table 2). Results are reported in Fig. 2 and show that changes from baseline to medium exposure levels are expected to generate reductions in health risks of about 2.6% on average in the study population. This impact increases to a 3.5% for high exposure levels compared to the baseline, though diminishing returns to scale can be intuited from the data, consistent with the literature (Pampalon et al., 2006). This implies that, all values held constant at the average, policies that increase availability of natural or semi-natural spaces for the citizens may generate health benefits up to 3.5% risk reduction.

Higher risk reductions are estimated for mortality compared to morbidity (+1.4%). As regards the type of illnesses, mental health has the largest impact on risk reduction (+0.39%) compared with the category "other diseases" (encompassing many diseases, such as cancer, diabetes, etc.). Though the coefficient is not significant, it shows a tendency of the importance of green areas on mental health in the current context where mental disorders are strongly contributing to the world disease burden (Burton and Rogerson, 2017). The broad and comprehensive category "general health" shows lower risk reductions (−1.7%) compared to "other diseases" addressing specific health conditions from exposure to green areas.

As for the demographic variables, gender does not affect significantly the impact, while adults and old people are those gaining slightly more from increased exposure to green spaces, compared to young people (< 16 years old), though the magnitude of the effect is small.

Socio-economic variables have also an impact on risk reductions. Income per capita was found to be moderators of the improvement in health. In studies conducted in poorer countries, increased exposure to green areas could lead to higher reduction in health risks, taking into account the publication bias (−2.5%). From a different methodological approach, other authors such as Wright Wendel et al. (2012) or

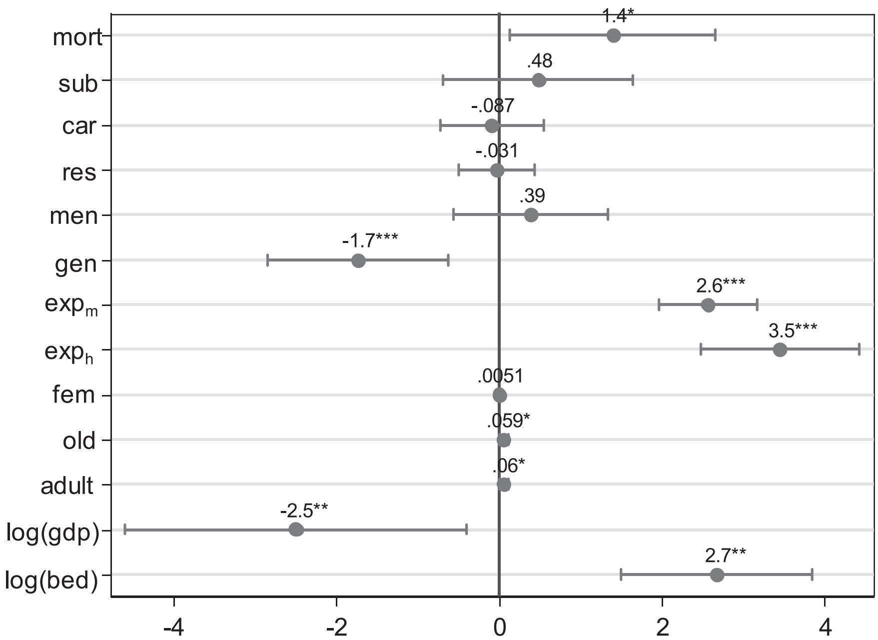

Fig. 2. Marginal effects for the Heckman model. Note: marginal effects calculated on the basis of the estimated model considering the non-linear effects and for mean values of quantitative variables and median values of dummy variables. Mortality (mort), Subjective (sub), Cardiovascular (car), respiratory (res), mental health (men), general health (gen), medium exposure (exp$_m$), high exposure (exp$_h$), female (fem), elderly (old), adults (adult), log income per capita (log(gdp)), log hospital beds per capita (log(bed)). Note: number of observations = 182.

Germann-Chiari and Seeland (2004) have also considered the role of access to green space in low-income groups and areas. Finally, health risk reductions are expected to be higher in countries with higher access to healthcare (measured as number of hospital beds per 1000 inhabitants in the country) (+2.7%).

Fig. 3 shows a simulation of expected HRR using OECD GDP per capita. It shows the negative and logarithmic decrease in impact associated to higher income levels as simulated using sample's average values as reference. It can also be seen in the figure the difference in impacts between higher and medium exposure levels. The graph marks average income as calculated from OECD countries, as well as the lower decile from the sample of OECD country average income. Potential for improvement therefore depends on context in the model drawn from this study. Richer countries require stronger improvements in their environmental conditions in order to achieve health improvements in their populations. While less developed countries can also benefit from stark environmental action, they can obtain these advancements with less effort. Investment on green areas may therefore be a strategy to alleviate health inequalities in poor areas. The findings suggest however that interventions may require important increases in green space available to obtain a certain level of health benefits.

4. Discussion and conclusions

The existing literature on the impact of exposure to green areas shows a high level of heterogeneity with respect to both the methods and indicators used for health and exposure to green areas. In this context, this study argues that it is important to consider both significant and no-significant results in the literature in order to construct an overall framework to study the relationship between green spaces and health. For this purpose, we performed the following steps: (i) literature review of studies with quantitative results on the health benefits associated with increased exposure to green areas, (i) construction of a database with standardized indicators for health and

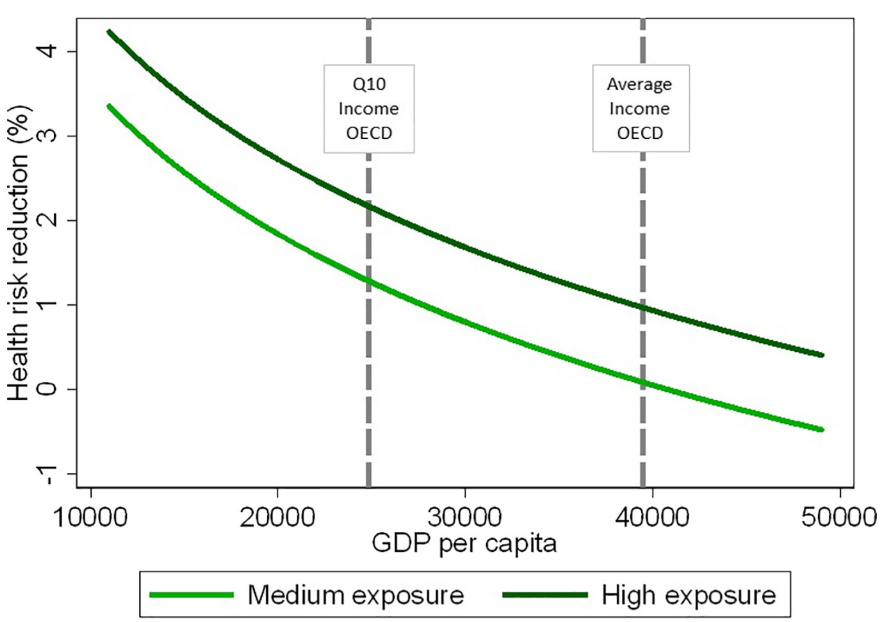

Fig. 3. Change in health risk reduction (HRR) in relation to GDP per capita for all-cause morbidity, 10% quantile (Q10) and average. Marginal effects are calculated for mean values of quantitative variables and median values of dummy variables. Source: own data and OECD Income Distribution Database (via http://oe.cd/idd). Note: number of observations = 182.

exposure levels, and (iii) econometric analysis using the Heckman Selection model to correct for the unobserved selection bias and analyse key emerging patterns from the literature.

Our results show that, while diverse, studies in the literature tend to find a positive correlation between green spaces and health benefits, especially strong for high levels of exposure. One of the most significant conclusion extracted from this analysis is the relevance of contextual factors. The notion that different contexts yield different interconnections is supported by the results obtained, which pointed towards income, education, and urbanization as possible factors affecting the results of the different studies.

A number of limitations have been identified in the approach proposed in this study. First, the approach does not consider the pseudo panel structure of the database. Due to the nature of our data (the observations responding to different health indicators), we do not have either the rationale (we cannot compare the observations among the different papers), nor the numbers of observations and associated degrees of freedom to adequately select the cohorts for the pseudo-panel.

Second, we are unable to consider the quality of green space as well as accessibility and usability given the lack existing in the literature in terms of quantitative analysis on health benefits. Third, heterogeneity of literature in relation to exposure required us to construct a qualitative indicator for this metric and ideally this would be standardized across the literature to allow for comparability in quantitative terms. This study has been performed in a field where the literature is growing but heterogeneous. While its intention is precisely to help in the task of having a general overview of the potential health benefits of green spaces in health, it highlights the need for a more common approach to metrics used in such studies.

Strengths and novelties of the proposed approach include the fact that this is the first time that the Heckman model has been used in a meta-analysis study to our knowledge, which guarantees a better approach compared to the Tobit model to synthetize the literature on environmental exposure to human health. This is also among the first studies that derive a marginal effect of exposure to green areas on health from existing studies in the literature that could be used for identifying health impacts in different contexts. Shanahan et al. (2016) found that the health benefit can be affected by the “dose” of nature experience. We find similar non-linear benefits.

Furthermore, this paper is based on the sound idea that the use of meta-analysis in reanalysing key but heterogeneous studies from the literature, taking into account both their significant and insignificant results, can provide a better understanding of the relationship between exposure to green spaces and human health. Finally, we highlight the unbiased nature of the results which can lead to better informed policy.

Our study has relevant implications over several social aspects. First, it opens a pathway for considering the co-benefits arising from adaptation to climate change using green spaces (Chiabai et al., 2018). The increase in the amount of available green space in urban areas has been proposed in order to adapt to several impacts of climate change such as increasing temperatures (Bowler et al., 2010; Doick et al., 2014; Harlan and Ruddell, 2011) or flood risks (Claessens et al., 2014; Opperman et al., 2009). Such measures are often referred to as Ecosystem-based Adaptation (EbA). The potential for health improvement could arise as a positive side effect or co-benefit of EbA strategies. An area where this could have implications is urban planning. The urban areas in developed countries are increasingly taking an ecological perspective towards development and new built areas include public open spaces including green areas. Literature suggests that green spaces are not optimally distributed among all citizens but that wealthier neighbourhoods dispose of higher amount of them (Germann-Chiari and Seeland, 2004; Mitchell and Popham, 2008). Therefore, development of green spaces in poorer neighbourhoods may decrease health inequalities within developed countries. Such reductions have direct economic impacts in the form of less medical expenditure, increased productivity and lower work absenteeism.

Yet, the most rapidly urbanizing areas are not located in such countries, and are often subject to social, economic and demographic pressures that do not allow for such measures to be implemented. It is precisely in these countries where quantitative studies are scarcer. The model predicts an inverse relation between income and health impacts, though the absence of studies in developing countries poses a pathway for future research. Context is central to the associated health outcomes of green spaces and adaptation strategies associated with green spaces should be tailored to the specificities of the area where they are applied.

This leads to another conclusion, that the effects of improving health through higher access to green space could lead to direct economic benefits. These benefits could take the previously mentioned forms of decreased medical expenditure, augmented productivity and less work absenteeism, which could be added to other benefits such as increase in property values, diminished flood risk, etc. Comprehensive economic valuations of green spaces that includes their impacts over health should be expected in future analysis. Cost-benefit analyses may otherwise underestimate benefits and lead to sub-optimal allocation of resources to green spaces. It is important that we properly identify these values, drawing on the use of techniques such as the Heckman modelling approach, so that policy can be appropriately targeted to protecting green space and, in so doing, protecting the health of the population.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2019.106401.

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