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The Importance of Neighbourhood Trees for Quality of Life: An Analysis of the Tree Canopy Cover and Social Indicators in Cambridge, UK

By

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18/09/2019

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ABSTRACT

Over the past 15 years, urban trees have been gaining more attention in academic research, local, and national policy for the benefits they provide to urban dwellers. These benefits include increasing resilience to climate change through water runoff retention and air pollution absorption, mitigating the Heat Island Effect, and contributing to human health and social cohesion through stress reduction and instilling a sense of place. Most of these benefits are delivered at a neighbourhood level, and have been shown to be particularly effective in areas of high deprivation. In these cases, an increase in tree cover can help buffer some of the effects of income inequality, such as high levels of stress and neighbourhood crime, creating a health-promoting living environment.

This project uses quantitative methods to assess the relationships between tree cover and some of these social and wellbeing benefits at a neighbourhood level in a medium-sized, rapidly developing city like Cambridge. The Index of Multiple Deprivation is used as a response variable, while the proportion of tree cover is used as an explanatory variable in a linear regression model. The aim is to identify the deprivation domains with the highest correlation with the tree cover. Then, the results are compared with the existing literature to try to identify some broader patterns.

Given that 77% of the land and 74.1% of the tree canopy in Cambridge are in private property, involving private owners in the management of the tree canopy is essential. A hedonic pricing model is used to assess whether property buyers value the tree cover near their property and are willing to pay more for a house with a higher proportion of tree cover.

The findings herein indicate that future policy should engage different local groups in their tree interventions. At the same time, more research is needed into the specific pathways by which tree cover influences human wellbeing in the urban space.

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TABLE OF CONTENTS

TABLE OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION AND PROBLEM DEFINITION

1.1 Background

Urban trees are increasingly being included in national, regional and local political frameworks that spell out the contribution that trees bring to urban life. National policy that applies to urban trees stems out of either planning or forestry departments. Figure 1 lists the national policy that refers to urban tree management in chronological order. Tree protection in land development was first inscribed into law explicitly in 1990, with the Town and Country Planning Act .The Act requires tree preservation to be embedded in the planning permission process, such that decisions taken by private land developers would not affect the community negatively (c., 1990). More recently, the National Planning Policy Framework (2012) explicitly referred to the natural capital and ecosystem services offered by urban trees, including economic ones. The Framework includes further provisions for the protection of ancient trees from development pressures (Ministry of Housing, Communities, and Local Government, 2019).

National policy relating to urban trees encourages integrated approaches to tree and woodland planting and management in and around towns and cities (DEFRA, 2007), highlights the need to value the social and environmental benefits of trees and to create market opportunities for them (DEFRA, 2013), and recognises the role urban and peri-urban woodlands play in ameliorating Heat Island Effect and increasing climate change resilience (Forestry Comission, 2017).

Policy	How it applies to urban trees
The Town & Country Planning Act 1990: Part 8 (Special Controls), Chapter 1 (Trees)	Section 197 – when granting planning permissions planning authorities are to preserve and plant trees; Sections 198-202 – Tree Preservation Orders (TPOs) defined; Sections 203-205 – TPO compensation; Sections 206-210 – legal consequences of TPO removal specified Sections 211-214 – trees in conservation areas Section 300 – Crown land disposal and TPOs
The Planning Act 2008	Amends sections of the 1990 Act relating to TPOs
Department for Communities and Local Government The National Planning Policy Framework, 2012	Identifies three dimensions to sustainable development: economic, social and environmental. In the social dimension, need to create a high quality built environment that supports the health, social and cultural wellbeing of its inhabitants. In the environmental dimension, the planning system needs to help improve biodiversity and mitigate and adapt to climate change.
The Climate Change Act, 2008	The world's first legally binding long-term framework to cut carbon emissions. It also creates a framework for adapting the UK to climate change, plus the role of trees to support such adaptation.
DEFRA A strategy for England's trees, woods and forests, 2007	Trees and woods in development and Green infrastructure are regarded as an important community resource that instils a sense of place.
DEFRA Forestry and Woodlands Policy Statement, 2013	Need for more trees and woodlands in and around towns and cities where they contribute to clean water, help manage flood risk and improve biodiversity.
Forestry Commission The UK Forestry Standard, 2017	This strategy and regulatory framework acknowledges the importance of urban woodland.
Forestry Commission Keepers of time: A statement of policy for England's ancient and native woodland, 2019	Sets out the government's policy towards woodlands and trees. Development proposals and strategies must ensure trees contribute to quality of life, sustainable development, wildlife and biodiversity, plus cultural heritage and landscape.

Planning Policy

Forestry Policy

Figure 1: National policy containing provisions that apply to urban trees

In practical terms, National Government guidelines specify that the integrated management of the urban forest falls under the responsibility of local government (Cambridge, C. C., 2015). Because of this, urban forestry faces a series of specific challenges despite the proven and recognised benefits that it brings to cities.

Firstly, reduction in Government funding and the public sector austerity agenda have led to budgetary pressure on local councils (Cambridge, C. C., 2015). At the same time, Cambridge is a rapidly growing city, which is expected to provide 33,000 new homes and 22,000 new jobs in and around its urban area by 2031 (Cambridge, C. C., 2015). This pressure on the Council's resources means that approaches to maintaining and enhancing trees should be connected to multiple issues of interest to the Council.

Secondly, while much tree advocacy highlights the benefits they bring to cities, in reality, a number of constraints specific to the urban context may limit the goods and services that trees are able to provide. Constraints such as land ownership, health and safety, site suitability, and interference with below-ground utilities, leads to a decrease in the number of trees that can be sustained in a locality (Moffat, 2016). In light of this, management of urban trees needs to take into consideration the socio-economic context of the place and work on a different timeframe than rural forestry.

1.2 Approach

Cambridge Council has a 10-year tree strategy running from 2016 to 2026. The strategy includes provisions for the role of trees in preserving the character and being part of the heritage of the city, as well as in cleaning the air, filtering storm water and lowering the city temperature (Cambridge, C. C., 2015). Resilience to climate change, as well as adaptation to urban expansion are central themes in the strategy. This strategy has an integrated urban forestry approach at its core, aiming to maximise the cumulative social, environmental and economic benefits that the tree population provides across the city (Cambridge, C. C., 2015). It is structured along three approaches(Cambridge, C. C., 2015):

1) To protect existing trees through the Council's regulatory responsibilities; and through the provision of tree management advice.

2) To enhance tree cover through the Council's regulatory responsibilities; through education; through public engagement; and through new tree planting.

3) To manage the Council's tree stock sustainably in accordance with current best practice and within the resource allocated.

Research in Cambridge to date has focused on the either climate change benefits of trees and their distribution across wards and land-use types (Wilson et al., 2013), or the civil society perceptions of local trees and their management and of the Council's tree strategy. A gap remains in research for a quantitative assessment of the socio-economic and health benefits of trees to the local population.

This paper represents, to our knowledge, the first attempt to quantitatively assess the connections between tree cover and socio-economic indicators in

Cambridge. The research presented here is of interest to academics, council officials seeking to develop tree interventions that also address the social indicators in the city, and policy makers developing strategies to improve the tree cover and social cohesion in the city.

This project was developed in two parts to capture the social and economic benefits that trees provide at the neighbourhood level. Firstly, an analysis of tree cover and social deprivation is conducted, to find any potential correlations and assess whether the patterns observed in Cambridge align with the existing research on the social and wellbeing effects of urban trees. While scientists, health professionals, and the popular opinion recognise the benefits that trees bring to urban lives, it can be challenging to evaluate and compare these benefits against conflicting priorities such as land development. Evidence from other cities indicate that trees are most protected and invested in when an economic case is made in their favour (Forestry Commission, 2010). This is of particular importance in Cambridge where 77% of the land is in private property (Wilson et al., 2013). For this reason, the second part of this project is concerned with analysing the connection between house price and tree cover around the property. A hedonic pricing method was chosen for this purpose, as it has the benefit of using real market prices and translating the environmental benefits of trees directly into monetary benefits to the house owner.

The chapters follow the two models in parallel. Chapter 2 presents a literature review of the components of the project. Chapter 3 establishes the data and methods to be used in the two parts. Chapter 4 details the 2 models that were built to quantify the relationship between tree canopy and indices of deprivation (4.1), and the hedonic pricing model (4.2). Chapter 6 presents a discussion of the results and their wider implications, and opportunities for further research are laid out. Chapter 7 concludes the paper by highlighting some policy implications that emerge from the results and discussion of our two models.

CHAPTER 2: LITERATURE REVIEW

2.1 Urban Tree Canopy: Definitions, Benefits, and Services

The tree canopy cover (tree cover hereafter) is most often defined as the area of leaves, branches, and stems of trees covering the ground when viewed from above. Many reasons can lead to a decrease in canopy cover, including changing climate, pest and disease, an ageing tree stock, population increase and urban intensification (Cambridge, C. C., 2015).

A report on land-use types and tree cover in Cambridge found that the main reason for variation in tree cover between wards was the difference in land-use for each ward. The highest tree cover was found in areas classified as Derelict, Neglected and Abandoned Open Space type areas, followed by Low Density Residential (LDR) and Medium Density Residential (MDR) areas (Wilson et al., 2013). This can mean that there is potential for the tree cover to be threatened as land development increases in the city. At the same time, a target increase in tree cover of 2% by land use and ward by 2030 is desired (Wilson et al., 2013)

While this research project is solely concerned with assessing the correlations between tree cover and social deprivation, reference will be made to some literature on green space more broadly. This is because some relevant findings come from studies that approach urban green space as a whole, and in some cases these studies can serve as a model for further research focusing on the tree cover in particular. Some other relevant concepts that include urban trees are “urban forest”, which typically refers to trees, as well as shrubs and other woody plant vegetation growing within a city, town, or suburb(Konijnendijk, 2003). This term is often used to describe areas of ecosystems which were inherited from wilderness leftovers or remnants. A contiguous area with over 10% tree canopy cover can be classified as urban forest by FAO definition (Salbitano et al., 2016).

Research into urban trees has been increasing over the past 10 years, in light of their climate change benefits and effects on physical and mental health. A systematic review into 115 original urban tree studies looked at the research locations, methods, and assessment techniques for tree services and disservices. These show that research into urban trees has been geographically concentrated, with 64% of the studies conducted in North America, and predominantly using quantitative research methods (91.3%), most frequently derived from natural science (60%)(Roy, Byrne & Pickering, 2012). This can be explained by the fact that urban forestry first emerged as a research focus in North America in the late 1960s. Urban trees are theoretically conceptualised as a subset of urban forests, because urban forests represent the total surface of urban trees, shrubs and grass (Roy, Byrne & Pickering, 2012). Initially, climate change considerations were not directly associated with urban trees (Moffat, 2016). The rising interest in urban trees and their management stemmed out of concern for increasing developmental pressures on green space, and the incidence of pests and diseases.

Connotations associated with trees and forestry affected the adoption of specialised management practices for trees in the urban space. Urban trees have not been readily associated with benefits to urban communities because of the widespread perception of trees as only associated with timber resources, forestry, and rural areas, and seen more as a liability in the city (Moffat, 2016). Urban trees require different management approaches than those in rural areas. For one, urban trees have reduced life spans because of continuing changes to the built environment, vandalism or premature felling due to perceived nuisances such as impeding sunlight or communication signals, or droppings on properties (Moffat, 2016). In contrast, rural forestry managers work on much longer timespans and with the goal to maximise economic return on investment(Moffat, 2016).

An increasing awareness of air pollution and climate change, and of the role trees play in mitigating their effects led to renewed efforts to understand the interactions between trees in woodlands and forests and the biosphere, hydrosphere and atmosphere starting from the 1980s. In Europe, increasing development pressures on green spaces and the growing demands for urban green functions that came with expanding urban boundaries led to an interest in more strategic and integrated approaches, such as urban ecology and urban green structure planning (Konijnendijk, 2003).

“Urban Forestry Practice” (Hibberd, 1989) was the first attempt to conceptualise the term in the UK. After its adoption, the UK became recognised as the first European stronghold of urban forestry (Konijnendijk, 2003). As it is understood today, urban forestry is defined as the management of single trees and tree populations in urban settings in order to maximise the social, environmental and economic benefits that trees provide (Cambridge, C. C., 2015). More recently, it has been argued that research on urban trees in the UK has a tendency to focus predominantly on adaptation to future climate change, while internationally scientists also highlight the role that canopy cover plays in reducing risk to current climatic threats (Wilson et al., 2013).

The importance of urban trees for human wellbeing came to the fore with the concept of ecosystem services. The ecosystem framework of goods and services was developed and gained central importance through large-scale projects such as the Millennium Ecosystem Assessment (Bates et al., 2005). Conceptually, there is a difference between ecosystem functions and ecosystem goods and services. The first refers to natural processes and their capacity to provide goods and services that satisfy human needs, while the later refers to the identifiable and measurable benefits that humans derive from those processes. The recognised ecosystem services that urban dwellers derive from local trees include: regulating services (air purification, carbon storage and sequestration, noise mitigation, storm water retention, temperature regulation, pest and disease regulation, pollination, soil protection), provisioning (wood fuel, biological and genetic resources, and to a lesser extent, food), cultural (health, nature connection, social connection, education, cultural significance and heritage), and supporting (habitats for species, soil formation, nutrient and water cycling) (Doick et al., 2018).

Roy et al (2012) draw a distinction between research that studies and discusses the ecosystem services of urban trees, and those that demonstrate them. The latter means that a study not only discussed a cost or benefit but the authors also provide evidence that such benefit actually exists(Roy, Byrne & Pickering, 2012). The demonstrated tree benefits in their review include: economic, social, health, visual and aesthetic benefits. Increasing property value was the most frequently demonstrated benefit of urban trees. Studies focusing on the economic benefits of trees also demonstrated reduced expenditure on air pollution removal, reduced expenditure on storm water infrastructure, saved investment in new power supplies, reduced heating and cooling costs, and reduced time on the housing market for the selling property(Roy, Byrne & Pickering, 2012). The only social benefit demonstrated was increased quality of life, while demonstrated health benefits were stress relief and respiratory disease prevention (Roy, Byrne & Pickering, 2012). Visual and aesthetic benefits demonstrated in literature so far were improved scenic quality, providing a sense of place and identity, creating seasonal interest, and providing privacy(Roy, Byrne & Pickering, 2012)

In light of the multiple benefits that urban dwellers derive from trees, and the complex challenges that they pose, more recent approaches to urban forestry management seek to integrate the socio-cultural and environmental values of forests with the more established economic ones(Konijnendijk, 2003).There has also been a shift from a “machine model” of urban forest management, based in managing individual characteristics and tree strands to a more complex, “organic model” , that seeks to manage entire ecosystems and interactions (Konijnendijk, 2003).

2.2 Effects of Trees on Social Deprivation and Human Health

There is now a substantial body of research on the relationship between green space and indicators of health and stress at local level. A study conducted in communities of high urban deprivation in Scotland, UK, found that the amount of green space in the neighbourhood was a significant predictor of stress levels among the population (Ward Thompson et al., 2016). Access to, views from the home, and frequency of visits to greenspace were found to be good predictors of good general health(Ward Thompson et al., 2016). Their study suggests that green space does not lead to stress mitigation through increased physical activity, but rather through enhancing place belonging and reducing social isolation, in cases where the green space can serve as place to gather (Ward Thompson et al., 2016).

The effects of urban green space on the residents' health are not always easy to demonstrate. They may not be visible across different scales or they may vary with the indicators used in the research. A UK study looking at the correlation between risk of death from all causes and city-wide proportion of green space found no correlation between the two after controlling for socio-economic factors(Bixby et al., 2015). Their findings suggest that the health effects of green space observed at neighbourhood level do not transfer to the city level. This difference in effect by scale of analysis can mean that green space in the immediate living environment has a bigger impact over health than the overall greenspace in the locality (Bixby et al., 2015).

Tree cover in particular has been shown to affect health and social cohesion indicators. Increased neighbourhood tree cover, independent of green space access, has been associated with better overall health, lower overweight and obesity rates, and improved social cohesion in urban spaces (Ulmer et al., 2016).

The research consensus seems to be around the role of tree cover in influencing health outcomes through mitigating stress levels and enhancing community cohesion, particularly in socially deprived neighbourhoods. The effects of tree cover on creating healthy living environments can be essential to improving living conditions in areas of deprivation, creating a health-promoting environment that buffers the effects of health and income inequality.

2.3 Mapping the Tree Canopy and Social Deprivation

The 2015 English Indices of Deprivation (IMD) was developed to update the 2010 one and uses data from the tax year 2012/2013. It is based on 37 separate indicators, organised across seven domains of deprivation, which are allocated distinct weights and calculated for every Lower Layer Super Output Area (LSOA) in England. Income and employment make up the largest share of the IMD, weighing 22.5% each.

It measures relative levels of deprivation in 32,844 small areas or neighbourhoods for the whole of England, which are ranked from 1 (most deprived) to 32,844 (least deprived) (Gill, 2015). It is important to note that the IMD represents a continuous scale of deprivation, meaning that there is no set threshold above which an area is considered 'deprived' or 'highly deprived' (Gill, 2015). Deciles are calculated by dividing the ranking into 10 equal groups, meant to represent the most deprived 10% of neighbourhoods nationally to the least deprived 10% of neighbourhoods nationally(Gill, 2015). Deciles are presented as numbers from 1 to 10, with 1 meaning the most deprived 10%, and 10 the least deprived 10%.

Recently, there have been several attempts to study the relationship between tree canopy cover and social deprivation in UK cities. Reports from Plymouth (Deeney, Turner & Sydenham, 2017) and Wycombe (Goodenough et al., 2018) compared ProximiTREE canopy cover data with census data on health, crime and the IMD. In these two studies, an average tree cover proportion was calculated for each area (18% for Plymouth, 25%, for Wycombe) and established as a cut-off point for the analysis. A t-test was then performed to assess the correlation between canopy cover and social deprivation deciles below and above this cutting point. Their findings showed positive correlations between above cut-off point tree cover and the IMD score, as well as some of its distinct domains(Deeney, Turner & Sydenham, 2017). These analyses indicated a general trend that areas with higher tree canopy tend to perform well on social indicators, therefore being characterised as less deprived.

Here we perform a more subtle analysis and seek to understand the shape of the relationships between canopy cover and various indicators of social deprivation. We use linear regression analyses. This allows us to regard the tree cover as a continuum and describe the entire relationship between the two variables.

2.4 Valuing urban trees

Most recent studies in the UK indicate that economic valuation of trees is the method with the highest potential to persuade policy makers and the public of the benefits of trees in the city (Rogers et al., 2015). Valuation techniques for nonmarket resources arose from the desire to represent the natural environment in the decision-making process, since it has been observed that natural settings are more readily eroded when their contributions to society are not quantified (Wolf, 2007). Valuation of urban trees is made difficult by the fact that they are public goods. In economics, it is held that consumption of a public good by one individual does not reduce the amount of the good available for consumption by others. This makes the public good prone to being under-produced, overused or degraded as a result of a lack of immediate remuneration for their existence (Wolf, 2007).

In our case, valuing urban trees can help local authorities to weigh costs against returns from development versus maintaining green areas, and to frame choices and make clear the trade-offs between alternative outcomes (Wolf, 2007).There are two types of methods for valuation of urban trees in environmental economics:

1) Revealed preference methods, which are based on the analysis of actual market data.

2) Stated preferences methods, which use surveys and direct interaction with people to obtain their explicit preferences with respect to open space.

Revealed preference methods were deemed suitable for situations where small changes and use value linked to the property market and recreation are investigated, while stated preference methods are more suitable for large-scale valuations to find non-use or total tree value(Price, 2007).

The revealed preference methods include: 1) travel cost method, 2) deferred and replacement cost analysis, and 3) market price (for environmental goods that are traded in markets, such as timber, cork and 4) hedonic pricing.

One central issue with valuing urban trees is that they are predominantly located on private property, therefore the planting and maintenance costs are covered by the homeowners, while the benefits can be enjoyed by the wider community (Siriwardena et al., 2016). This discrepancy can cause property owners to not prioritise tree planting and maintenance of existing trees, leading to socially suboptimal local tree cover. Therefore, understanding the benefits that accrue to the individual property owners, as well as the local community, can help the local council design targeted plans and programs to enhance the quality of life of the city residents and justify the costs for such programs. Moreover, identifying potential financial benefits that property owners can derive from their local tree cover can help engage them in maintaining and enhancing the tree cover on their property.

2.5 Hedonic Pricing Method

Hedonic pricing method has been successfully used to measure the impact of environmental factors such as noise level, water pollution and air particulates on the value of a property(Freeman, 2003). The foremost advantage of the hedonic method over other valuation methods is that it uses real market transactions instead of hypothetical questionnaires or indirect assessments. The hedonic pricing method calculates exclusively the benefits that accrue to property owners from the tree cover on or near their property. Hedonic property price models use property characteristics and house sale prices to calculate the implicit price of a characteristic. The implicit price of a characteristic in hedonic pricing is the additional amount property buyers will pay for a housing bundle with a higher level of that characteristic while holding all other property characteristics constant (Freeman, 2003). This method assumes that differences in property prices are due to differences in housing characteristics. Assuming that the price paid for a good-in this case, a house- is the sum of what is paid for each of its characteristics, the hedonic method calculates the monetary value of each characteristic by observing the differences in the market price of commodities sharing the same attributes (Dimke, Kelley C., 2008).

A meta-study of US hedonic pricing studies found that the tree cover density that maximises implicit prices (38%) is greater than property-level or near and around property tree cover density (30%)(Siriwardena et al., 2016). This means that property owners preferred more tree cover in the areas where they live, work, shop, and recreate, rather than on their private property(Siriwardena et al., 2016). This is due to the maintenance costs and perceived risks (storms, fires) associated with private trees being predominantly bore by the property owners. When these costs and risks were shared with other property owners or taxpayers, higher levels of tree cover were preferred (Siriwardena et al., 2016). The US average implicit price for a 1% change in tree cover was $239 for positive implicit prices, and $156 for negative implicit prices. Sites with older tree growth had higher implicit prices compared to younger trees, suggesting that people value living in areas with mature trees more, potentially due to increased shading and enhanced visual appeal (Siriwardena et al., 2016). The preference for older trees identified across studies coincides with the fact that older trees tend to be more ecologically viable than younger ones: they store more carbon, can abate larger quantities of air pollutants and tend to support established ecosystems which makes them more valuable for biodiversity purposes. A higher monetary value of mature trees can help persuade land developers to protect and restore existing trees, rather than cutting them down and planting young ones. The relationship between tree cover and house price in this meta-study was non-linear, with price paid for tree cover dropping after a certain threshold.

CHAPTER 3: METHODOLOGY

3.1 Data

Bluesky ProximiTREE aerial photography data on tree canopy and tree height from 2008 was provided by Cambridge City Council.

Boundary data was downloaded from the Ordnance Survey website. The boundary layers used for mapping were City wards borders and LSOA borders from 2011 census data. LSOAs are census units used in England and Wales that were developed for the output of census estimates. For this reason, they are designed to have similar population sizes and be as socially homogenous as possible based on tenure of household and dwelling type. The minimum population for an LSOA is 1000 and the mean is 1500. These characteristics were useful to this analysis, as it meant that population density was relatively constant throughout the study area. The fact that they are designed to be demographically homogenous made them readily useful for studying the relationship between social deprivation and tree cover. LSOAs align to local authority district borders, tend to be constrained by obvious boundaries such as major roads, and typically consist of entirely urban postcodes or entirely rural postcodes. There is an LSOA for each postcode in England and Wales, which was useful in translating the proportion of canopy cover from the first step of the project to the estimation of tree cover around a property for the hedonic analysis step. There are 69 LSOAs in the Cambridge urban area. LSOAs have a mean area of 58.97 ha, and a median area of 31 ha.

ArcGis 10 and QGiS 3.4 were used for the mapping process. The regression model was built using the R software package. Decile numbers were used for the regression analysis part of the project, as they are independent from the rest of the LSOAs in the country; by comparison, rankings and scores are attributed to each individual LSOA in the country, meaning that there would be considerable gaps between the LSOAs in Cambridge.

For the hedonic analysis, house sale data was provided by Cambridge Council from the Hometrack housing intelligence system (*Home Track;* 1999). These records included data on house sale price, total property area size in square feet, number of bedrooms, year built, the house type (detached, semi-detached, terraced), and condition of the house at the time of the transaction (new or not new). Additionally, the plot sizes of the houses were measured using Cambridge Council's own records. The tree cover was inferred using the calculations from the previous step. A proportion of tree cover was attributed to each property by matching its postcode to the corresponding LSOA code. While many previous studies using hedonic analysis used population density as a neighbourhood characteristic, population density is not referred to in this model. Population density is calculated for the city as a whole and in Cambridge it is estimated at 250 people per square kilometre. For this reason, it could not be included as a variable in our hedonic model which looks at a smaller scale.

We use house sale data from 1995 to 2019. The data is separated into 2 parts: 1995-2008 and 2009-2019. 2008 was chosen as cut-off point in our data for 2 main reasons:

1) The tree canopy data was captured in 2008. Hence, any correlation with house price data can be established most accurately around this period.

2) The 2008 financial crisis caused great changes to the UK housing market.

Therefore, we expect the 1995- 2008 model to reflect most accurately and reliably the relationship between tree canopy and property prices in Cambridge.

3.2 Methods

3.2.1 Mapping the tree canopy and calculating the proportion of tree cover

Ward data was used to create the boundaries of the project. The inner boundaries of the wards were then dissolved to obtain the polygon layer of the city limits. This layer was then combined with LSOA boundary data from 2011, and then joined with the IMD data. Tree height and tree canopy layers were joined to centre the tree canopy inside the LSOA polygons and avoid double-counting of the trees along polygon boundaries. Then, the proportion of tree cover was calculated by dissolving the individual tree canopies and calculating their total area within each LSOA.

3.2.2 The Index of Multiple Deprivation

The H_0 to test is that the proportion of tree cover has no effect on the IMD and the individual domains of deprivation. Linear regression is performed for the deciles in each subdomain and the IMD as a whole. As the data plots indicated a curvilinear relationship, a quadratic model was used for the IMD and all but one subdomain.

The formula for the model can be written as follows:

$$y = \beta 0 + \beta 1x + \beta 2x^2$$

Where y = the IMD decile and x=percent tree canopy cover

3.2.3 Hedonic Pricing

Flats were excluded from the model for accuracy purposes, as flats would have different characteristics and price points than houses. Dummy variables were used for the type of house (detached, semi-detached, terraced) and for the 5 postcode areas in Cambridge: CB1, CB2, CB3, CB4 and CB5. Except for CB1, all the other postcode areas extend beyond the city limits. The postcodes in our study (Figure 2) refer to the Cambridge city area only, but the population statistics associated with the postcode areas are referred to for context. Average household income was initially included in the model, but it was later removed due to collinearity with the post-code variables.

Postcode	Number of properties in our study		Unemployment rate	Population	Average household income
	1995-2008	2009-2019			
CB1	276	1002	3.0%	80,206	£44,720
CB2	85	463	2.4%	139,915	£58,760
CB3	10	102	2.2%	16,104	£56,680
CB4	155	606	3.5%	41,924	£53,040
CB5	56	193	3.2%	12,092	£46,800

Figure 2: Postcode area characteristics

We assumed ownership of the land with the tree canopy to follow the pattern described in (Wilson et al., 2013), namely 74.1% of the canopy cover to be in private property, 16.3% under council management, and 9.6% along the highway. As the majority of the tree cover was in private property, we calculated the tree cover around a sold property regardless of its ownership. To do this, we linked the house data with the proportion of tree cover calculated in the tree mapping stage (4.1) by matching the LSOA code of the property to the property postcodes in our sample. Hedonic regression has been used previously to determine the impact of nearby trees on the house property with mixed results. Some studies found that people prefer a higher tree cover in the area around their homes (Sander, Polasky & Haight, 2010; Siriwardena et al., 2016). Hedonic studies carried out using field measurements of the tree cover on the homeowners land showed positive significant results (Dimke, Kelley C., 2008). This approach was beyond the scope of this project. As a result, the tree cover measure used in this model is the proportion of tree cover on a 31ha area around the property. This model did not differentiate between tree species, or the distribution and composition of the tree canopy.

Typically, hedonic regression models use variables relating to the house attributes, area characteristics (such as neighbourhood average income, schools, etc.), and environmental characteristics. Consistent with existing models, we use number of bedrooms, floor space area, plot size, building age and type of building as house characteristics. Neighbourhood characteristics are condensed into post-code areas, which are associated with a distinct average household income and unemployment rate. Other variables were not included to avoid collinearity issues. Neighbourhood characteristics such as distance to schools, shopping areas, and transit stations have been shown to have both positive and negative effects on house price, as they increase footfall in the area (Sander, Polasky & Haight, 2010). Month of the year was included in the model because in some studies differences were observed between colder and warmer months and the effects they had on the size of the canopy and the tree cover coefficient (Cho, Poudyal & Roberts, 2008; Dimke, K. C., 2008)

The selling price of the house represents the dependent variable, and it is taken to reflect the market price of that property. We used the real sale prices of the property, rather than current assessed values because the sale prices represent actual market values and are preferred in hedonic models for their accuracy (Sander, Polasky & Haight, 2010). The independent variables are the attributes of the house. The hedonic pricing method does not have a have a pre-defined functional form. Linear models are most frequently used due to the ease of interpretation.

An OLS hedonic regression model was used to assess the effect of the local tree cover on house sales in Cambridge. We tested the data for rese and found that the variables for floor space, plot size, detached and semi-detached house, postcode areas CB2, CB3, CB4, and CB5, as well as the house price showed severe positive skewness. The tree canopy showed moderate skewness to the right. The house sale year showed a severe negative skew. Natural log values were used for the variables that showed severe (>1) skewness. We applied the same treatment to the tree canopy variable because the tree cover mapping step indicated non-linear behaviour. The post-code and house type dummy variables showed severe skewness, so a square root term was used for the semi-detached, detached, CB2, CB3, and CB4 variables in the equation.

The variables used in this model are defined as follows:

Property characteristics
BD = number of bedrooms
FLOORSP = total floor area of the property in square feet
PLOTSZ = total plot size of the property in square feet
SY = the year when the transaction was recorded
AGE = sale year – built year
S = dummy variable for semi-detached house; 1 if semi-detached, 0 otherwise
D = dummy variable for detached house; 1 if detached, 0 otherwise
T = dummy variable for terraced house; 1 if terraced, 0 otherwise

Neighbourhood characteristics
CB1 = dummy variable for houses in the CB1 post code area; 1 if CB1; 0 if otherwise
CB2 = dummy variable for houses in the CB2 post code area; 1 if CB2; 0 if otherwise
CB3 = dummy variable for houses in the CB3 post code area; 1 if CB3; 0 if otherwise
CB4 = dummy variable for houses in the CB4 post code area; 1 if CB4; 0 if otherwise
CB5 = dummy variable for houses in the CB5 post code area; 1 if CB5; 0 if otherwise
Environmental characteristics
MONTH = month of the year when the property was sold
TC = Proportion of tree cover in the LSOA the house falls under
Dependant variable
P = house sale price

1995-2008

We conducted several models and performed a RMSE test to assess their accuracy at describing the data. The selected model (RMSE = 0.31) is a log-linear model.

The regression equation can be written as follows:

$$lnP_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_z x_{ni} + \varepsilon_i$$

Where lnP_i is the natural logarithm of the sale price of the property, $x_{1i}, x_{2i}, \dots x_{ni}$ are the characteristics of the property, and ε_i is the error term for the equation.

Log-linear regressions are widely used for hedonic models. Log-linear hedonic models reduce the heteroskedasticity issues of the variables and can be used when there are reasons to assume that the relationship is not linear. Many studies have indicated that the relationship between tree cover and house price may not be linear; this can be due to the house buyers valuing nearby tree cover up to a point, after which it declines in value (Siriwardena et al., 2016), or because in reality, home buyers cannot treat individual housing attributes as discrete items from which they can pick and mix until the desired combination of characteristics is found (Kong, Yin & Nakagoshi, 2007).The log-linear model has been used successfully by the ONS to estimate the average value of blue and green spaces in relation to average house prices in the UK (Anderson, 2018) and in cases where data on house properties was incomplete (Sander, Polasky & Haight, 2010).

2009-2019

There were 2375 records for the years 2009-2019. This dataset had different skewness indicators from years 1995-2008. Floorspace, plot size and the dummy variable for detached house displayed severe positive skewness. Postcode areas CB2, CB3, CB4, and CB5 displayed severe positive skewness. House sale price also displayed severe positive skewness. In contrast to the 1995-20018 dataset, sale year, semi-detached house and tree canopy showed low to moderate skewness.

Since we cannot guarantee that the tree cover data collected in 2008 is valid for the 2009-2019 interval, this second regression model was developed for comparison in the evolution of house attributes and house prices after 2008. A log-linear model was tested, to keep consistent with the 1995-2008 model. The log-linear model yielded an R^2 of 0.57, and a high RMSE. Other models were tested and their RMSE compared. A quadratic model was tested, but it did not improve the coefficient of determination. The dataset for this second interval showed higher variability so all the variables were standardised using the “scale” function in R. An OLS model was then used.

The formula for this model can be written as follows:

$$P_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_z x_{ni} + \varepsilon_i$$

With P_i – the standardised sale price variable, $x_{1i}, x_{2i}, \ldots x_{ni}$ the standardised values of the characteristics of the property, and ε_i the error term for the equation.

CHAPTER 4: RESULTS AND ANALYSIS

4.1 The Index of Multiple Deprivation and the Tree Canopy

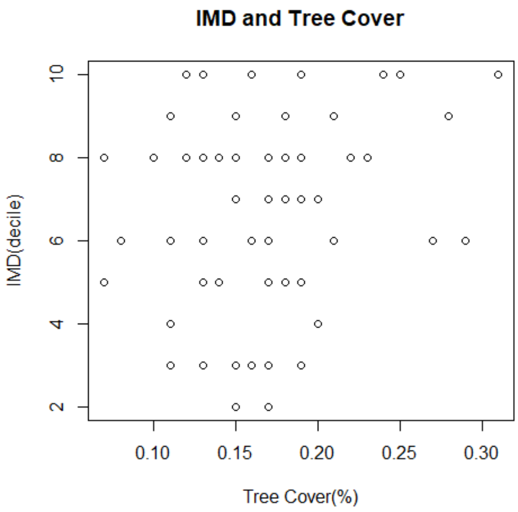
The data points were first plotted in R, and a best-fit line was determined. The lowess function was used to fit a smooth curve through the data points in the scatterplot. This step was performed to help visualise the line of best fit for the data.

Then, a quadratic regression model was used to determine the regression function of the relationship for each domain with the domain of deprivation as the response variable and the tree canopy cover as the independent variable. Since LSOAs are designed to have similar numbers of people and households, controlling for population was not necessary for this model.

Decile	DF	R-squared	Residual Standard Error	F statistic	P-value	Reject Ho?	Explanation
IMD	2 and 66	0.1214	2.174	4.561	0.01396	Yes	Tree canopy cover is associated with 12% of the variation in IMD.
Income Deprivation	2 and 66	0.07565	2.442	2.701	0.07459	No	No relationship between tree canopy and income deprivation found.
Employment	2 and 66	0.05439	2.438	1.898	0.1579	No	No relationship between tree canopy and employment deprivation found.
Adult Skills and Training Deprivation	1 and 29	0.2104	1.694	7.727	0.009453	Yes	Tree canopy cover is associated with 21% of the variation in adult skills.
Health	2 and 66	0.03801	2.531	1.304	0.2784	No	No relationship between tree canopy and health deprivation found.
Crime	2 and 66	0.16	2.09	6.35	0.003	Yes	Tree canopy cover is associated with 16% of the variation in crime.
Barriers to housing and services	2 and 66	0.0068	2.128	0.2263	0.7981	No	No relationship between tree canopy and barriers to housing and services found.
Living Environment Deprivation	2 and 66	0.0069	1.731	0.2289	0.7961	No	No relationship between tree canopy and living environment deprivation found.
IDACI	2 and 66	0.0468	2.614	1.62	0.2057	No	No relationship between tree canopy and IDACI found.
IDAOPI	2 and 66	0.05681	2.493	1.988	0.1452	No	No relationship between tree canopy and IDAOPI found.

Table 1: Total domains regression results

The results indicate a significant positive correlation between tree canopy cover and IMD, Crime decile, and Adult Skills and Training Deprivation decile (Table1). This means that an increase in tree canopy was correlated with lower deprivation levels (higher decile number). The best fit line for the IMD and Crime dependent variables was provided by a quadratic model. Adult Skills and Training Deprivation was the only decile that was best described using a straight line, therefore a first order linear regression model was used in this case.



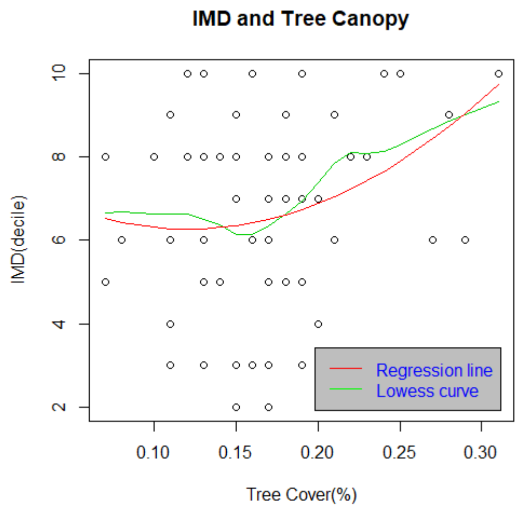


Figure 3: IMD Scatter Plot

Figure 4: Smoothened curve and regression line

Index of Multiple Deprivation

Tree canopy cover is significantly associated (p=0.01) with 14% of the variation in IMD distribution across the LSOAs in Cambridge City.

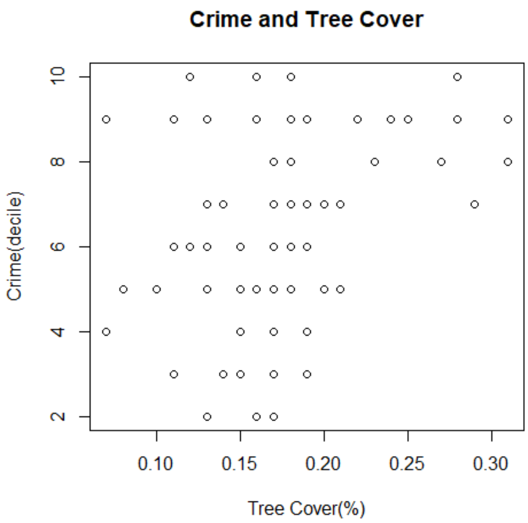


Figure 5: Crime Scatter Plot

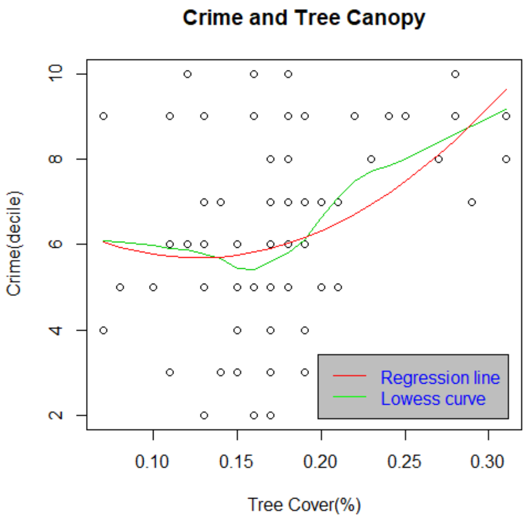


Figure 6: Smoothened curve and regression line

Crime

Tree canopy cover was found to be associated with 16% of variation in crime deciles in Cambridge City (p=0.003).

Adult Skills and Training Deprivation

The Adult Skills domain showed the strongest relationship with tree canopy cover in the study. Tree canopy cover is significantly correlated (p=0.009) with 21% of the variation in adult skills deprivation across all the LSOAs in Cambridge City. The data relating to decile 10 was removed from the scatterplot, as it was affecting the normal distribution of the data.

After removing the data points for decile 10, 30 data points were left, corresponding to deciles 4 to 9.

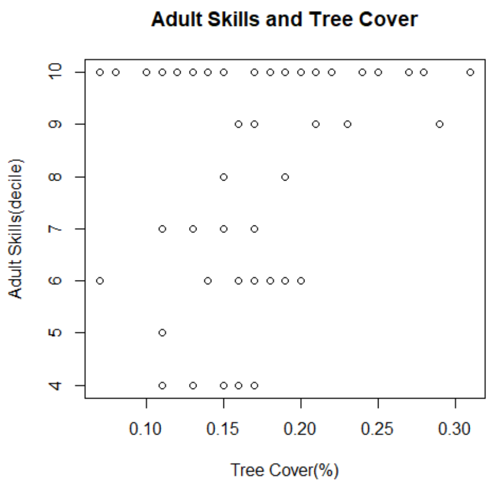


Figure 7:Scatter plot with all deciles

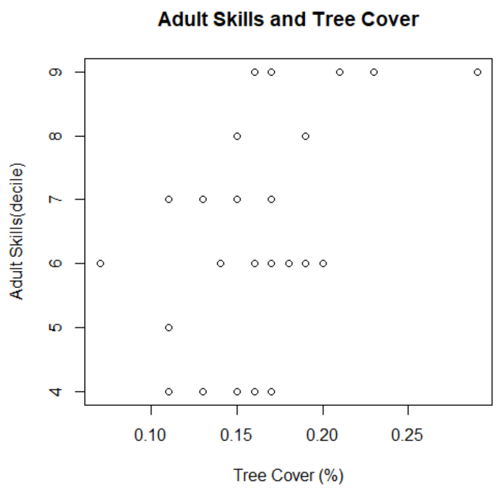


Figure 8: Scatter plot with decile 10 removed

Figure 5 illustrates the distribution of adult skills deprivation in relation to tree canopy cover, while Figure 6 shows the distribution after decile 10 -the least adult skills deprived- here interpreted as the highest educated- was removed.

The line of best fit in for this scatterplot was a first order linear regression line (Figure 7).

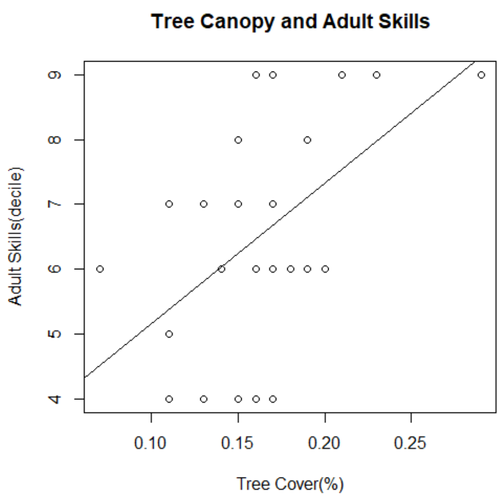


Figure 9: Adult Skills and tree canopy regression line

4.2 Hedonic Regression

1995-2008

Our model accounts for 69% ($R^2 = 0.69$) of the variation in housing price ($p < 0.001$). The variables with the highest explanatory power were the floor space, the type of building, postcode area and canopy cover. Increases in floorspace were associated with higher house sale price. A sale date closer to 2008 was associated with a higher sale price. Semi-detached houses were negatively correlated with house sale price. Postcode areas CB2 and CB3 were both positively correlated with higher house price. Tree cover was positively correlated with a higher house price.

Estimate Std. Error t value Pr(>|t|)

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.213e+03	6.454e+01	-18.798	< 2e-16	***
BD	4.172e-02	2.281e-02	1.829	0.06790	.
FLOORSP	7.942e-01	5.542e-02	14.329	< 2e-16	***
PLOTSZ	2.249e-02	2.022e-02	1.112	0.26647	
AGE	3.009e-04	2.932e-04	1.026	0.30525	
SY	1.604e+02	8.495e+00	18.877	< 2e-16	***
S	-1.403e-01	3.258e-02	-4.306	1.94e-05	***
D	4.035e-02	4.833e-02	0.835	0.40410	
CB1	1.514e-02	4.680e-02	0.323	0.74647	
CB2	1.864e-01	5.666e-02	3.289	0.00106	**
CB3	2.101e-01	7.701e-02	2.728	0.00656	**
CB4	-8.933e-02	4.981e-02	-1.793	0.07341	.
MONTH	5.423e-03	3.920e-03	1.383	0.16704	
TC	1.428e-01	5.132e-02	2.782	0.00557	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.314 on 602 degrees of freedom

Multiple R-squared: 0.6932, Adjusted R-squared: 0.6866

F-statistic: 104.6 on 13 and 602 DF, p-value: < 2.2e-16

Figure 10: Hedonic regression results for years 1995-2008

The number of bedrooms showed no significant correlation with house price. The age of the building showed no significant correlation with house price.

The type of house was significantly correlated with house price. Due to multicollinearity associated with the high number of dummy variables, terraced house (T) was held as a constant while detached (D) and semi-detached (S) house sales were assessed against it. Semi-detached houses were significantly negatively correlated with house price.

A similar treatment was applied to postcode areas. CB5 was taken as reference, while all the other postcode areas were assessed against it. CB1 showed no significant correlation with house price. CB2 showed significant positive correlation with sale price. CB3 postcode area showed significant positive correlation with house price. CB4 showed no significant correlation with house price.

No significant correlation was found between house sale price and the month of the year when the transaction was registered.

Tree cover shows a positive correlation with house price. In the log-linear regression model, the coefficients represent the elasticity of price with respect to change in the presence and quantity of the variable. For tree cover, this means that for a 1% increase in tree cover in a 50ha area around the property we expect to see a 1.4% increase in the house price while all the other characteristics are held constant. For an average price of £271,188, a 1% increase in tree cover we can expect an increase in house sale price of £3,796.63.

We tested for correlation between the independent variables in our model using a Variance Inflation Factors (VIF) test in R. Conventionally, an VIF score above 5 indicates critical correlation between variables. A score of 1 indicates no correlation, and a VIF between 1 and 5 shows moderate correlation. The values indicated that some moderate correlation existed between some variables, but not high enough to use corrective measures.

The VIF scores for age of the building, sale year, month of the year, and tree canopy showed no collinearity. All other variables showed low or moderate collinearity.

Variable	VIF
BD	2.401332
FLOORSP	2.552909
PLOTSZ	1.393471
AGE	1.066979
SY	1.097483
S	1.376098
D	1.358730
CB1	3.383825
CB2	2.432437
CB3	1.716465
CB4	3.062845
MONTH	1.048418
TC	1.196544

Figure 11:VIF values for collinearity. <1 insignificant, 1-5 moderate, >5 high

2009-2019

The OLS model using standardised data for this interval accounted for 70% of variation ($R^2 = 0.70$, $p < 0.001$). The variables with the highest explanatory power were floorspace, plot size, age of the building at the time of the purchase, sale year and the post code area.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.572e-15	1.112e-02	0.000	1.00000	
BD	-8.115e-02	1.667e-02	-4.869	1.20e-06	***
FLOORSP	7.735e-01	1.755e-02	44.064	< 2e-16	***
PLOTSZ	1.375e-01	1.286e-02	10.698	< 2e-16	***
AGE	1.043e-01	1.318e-02	7.915	3.76e-15	***
SY	-1.433e-01	1.121e-02	-12.786	< 2e-16	***
S	-3.391e-02	1.274e-02	-2.662	0.00783	**
D	7.873e-03	1.317e-02	0.598	0.55003	
CB1	4.177e-02	2.172e-02	1.923	0.05462	.
CB2	1.332e-01	1.981e-02	6.721	2.26e-11	***
CB3	1.038e-01	1.445e-02	7.183	9.11e-13	***
CB4	-9.101e-03	1.992e-02	-0.457	0.64780	
MONTH	-1.752e-02	1.127e-02	-1.554	0.12034	
TC	1.767e-02	1.211e-02	1.460	0.14446	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Residual standard error: 0.5419 on 2361 degrees of freedom					
Multiple R-squared: 0.708, Adjusted R-squared: 0.7064					
F-statistic: 440.3 on 13 and 2361 DF, p-value: < 2.2e-16					

Figure 12: Hedonic regression results for years 2009-2019

No significant correlation between tree cover and month of the year was found in this model.

The tree canopy had a low VIF score, indicating that no correlation existed between tree canopy and other variables. The VIF scores for number of bedrooms and floor space indicate that some moderate correlation is present.

Tree cover, age, sale year, and month of the year showed little to no correlation with the other variables.

Postcodes CB1, CB2, and CB4 showed moderate correlation with other variables.

Variable	VIF
BD	2.364531
FLOORSP	2.643819
PLOTSZ	1.387896
AGE	1.381896
SY	1.014580
S	1.409575
D	1.423378
CB1	3.817653
CB2	3.173568
CB3	1.687792
CB4	3.210269
MONTH	1.025697
TC	1.176449

Figure 13:VIF values for collinearity. <1 insignificant, 1-5 moderate, >5 high

CHAPTER 5: DISCUSSION

5.1 Results and Implications

5.1.1 The Index of Multiple Deprivation

The IMD combines information from 7 domains to produce an overall relative measure of deprivation. Our model found a significant positive correlation between tree cover and the IMD. This means that as tree cover increases, social deprivation is expected to decrease. These findings are consistent with other studies looking at IMD and canopy cover using a t-test method(Deeney, Turner & Sydenham, 2017; Goodenough et al., 2018).. Research in Plymouth and Wycombe using t-test methods showed a general trend towards a decrease in deprivation levels as tree cover increased.

Some limitations arise from using the IMD and its domains as variables in our model:

i. The IMD is a relative measure of deprivation, not an absolute one. This means that the scores do not relate straightforwardly to the proportion of the population experiencing deprivation. For instance, an area with a score of 40 on the IMD is not necessarily twice as deprived as an area with a score of 20.
ii. Due to low R^2 values, which are characteristic of studies involving human behaviour, the results of this regression analysis can only indicate correlation. A causal relationship cannot be confidently established between tree canopy and social deprivation. However, there are substantial numbers of reliable research findings that align with and can substantiate our findings.
iii. Our data sample was limited to 69 LSOAs to align with the administrative boundaries of the city. A clearer pattern may be possible with a bigger sample size.

5.1.2 Crime

The Crime domain measures the risk of personal and material victimisation at local level (Smith et al., 2015). It is comprised of 4 indicators: 1) violence: the rate of violence per 1,000 at-risk population, 2) burglary: the rate of burglary per 1,000 at-risk properties, 3) theft: the rate of theft per 1,000 at-risk population, 4) criminal damage: the rate of criminal damage per 1,000 at-risk population.

Our results are consistent with findings from other urban contexts. A significant negative correlation between tree canopy cover and the crime domain has been found in previous studies in Plymouth and Wycombe (Deeney, Turner & Sydenham, 2017; Goodenough et al., 2018). A study using a spatial correlation model in Chicago found a significant negative correlation between tree canopy and assault, battery, robbery, and narcotics after accounting for potential confounding socioeconomic variables (Schusler et al., 2018). Tree canopy cover has been shown to be associated with lower rates of both violent and property crime. A study in New Haven, Connecticut showed that a 10%

increase in tree canopy cover was associated with a 15% decrease in violent crime and 14% decrease in property crime (Gilstad-Hayden et al., 2015). New Haven is a mid-sized university city of comparable size and population to Cambridge. The study used spatial analysis methods to assess the associations between tree canopy cover and violent (murder, rape, robbery and assault), property (burglary, theft, motor vehicle theft and arson) and total (violent + property) crimes(Gilstad-Hayden et al., 2015). Their findings indicate a strong association between higher canopy cover and lower rates of violent, property and total crime and independent of educational attainment, median household income, socio-demographic factors, population density, vacancies and irrespective of proximity to high-crime areas(Gilstad-Hayden et al., 2015). This means that increased canopy cover is correlated with lower levels of crime across all socio-economic, demographic, and income groups.

Some explanations put forward are that trees draw more urban residents to spend time outdoors, therefore increasing the “eyes on the street” surveillance, strengthen social cohesion among neighbours, and discourage criminals by indicating that residents will intervene for each other (Schusler et al., 2018).

A UK-wide study using quantitative spatial statistical methods and qualitative interview analysis assessed the relationship between contact with nature, social cohesion, and crime across different geographical areas and demographic groups (Weinstein et al., 2015). Their work draws on a randomly selected sample from a large cohort and weighted to be nationally representative and ward-level greenspace data. Their findings indicate that 8% of the variability in community cohesion could be explained by subjective experiences of local nature, while individual predictors such as income, gender, age and education together accounted for only 3% of independent variance (Weinstein et al., 2015). Therefore, greenspace can potentially influence social cohesion more than social predictors like income, gender, age, and education levels.

Further research in Cambridge could use a similar approach to analyse the relationship between tree canopy, reported social cohesion and crime statistics at city level. Next steps in research in the area could include longitudinal studies that follow the relationship between canopy cover and crime over time, as well as studies that look at the residents’ use and perception of their neighbourhood and workplace trees and greenspace. This would clarify the relationship between trees and crime and the pathways that lead to negative correlations across different geographies and demographic groups.

5.1.3 Adults Skills and Training Domain

The decision to remove data related to the 10th decile of this domain from the analysis was motivated by the context of Cambridge as a university city. What can be seen in the plot is that the highest educated are distributed evenly across all levels of tree canopy cover, which in this context can be interpreted as PhD or Post-Doctoral students who would temporarily live in any area of the city. This assumption was strengthened by the fact that this treatment did not have a similar effect on any other domain.

The Education, Skills and Training Deprivation Domain measures the lack of attainment and skill in the local population (Smith et al., 2015). It is composed of two sub-domains: one measuring education, skills, and training in children and young people and one in adults. A regression analysis was performed for the domain as a whole, as well as for the two sub-domains. These were created to represent the ‘flow’ and ‘stock’ of educational disadvantage within an area, where the ‘children and young people’ sub-domain measures the attainment of qualifications and associated measures (‘flow’), and the ‘skills’ sub-domain measures the lack of qualifications in the resident working-age adult population (‘stock’) (Smith et al., 2015).

The Adult skills sub-domain is composed of 2 indicators: 1) the proportion of working-age adults with no or low qualifications (women aged 25 to 59 and men aged 25 to 64) and 2) English language proficiency: the proportion of working-age adults who cannot speak English or cannot speak English well (women aged 25 to 59 and men aged 25 to 64). The Adult Skills sub-domain uses the proportion of adults with no or low qualifications and/ or lack of English language proficiency for indicators, with no other combination within the sub-domain (Smith et al., 2015). This means that the indicators for this subdomain relate directly to the proportion of adults experiencing skills deprivation within a given LSOA.

It is surprising that our model showed a significant correlation between tree canopy and the adult skills sub-domain, yet not the Education, Skills and Training domain as a whole, or the children and young people sub-domain. Some explanations may arise from how the domain is weighted and the sample size in our study. Our results in this domain do not fully align with existing research in the UK. A correlation was previously found between canopy cover and educational attainment in Wycombe using GCSE achievement measures and the number of pupils achieving the expected level in each of the 17 early learning goals at Middle layer Super Output Areas (MSOA) scale (Goodenough et al., 2018). This indicates that a larger sample size may yield a better correlation model and that the children and young people sub-domain indicators may not have been suited for the purposes of this study.

There are, however, characteristics specific to Cambridge that can influence the relationship observed between canopy cover and adult skills deprivation. A report from the think tank Centre for Cities placed Cambridge city first among most unequal cities in the UK. The ranking was based on the Gini coefficient, which the think tank calculated ONS income data. It was found that the top 6% of earners who live in Cambridge take home 19% of the total income generated by residents, while the bottom 20% of people account for just 2% of the total. This statistic coupled with the fact that the city has the highest proportion of highly-educated residents in the UK, means that the distribution of skills is tightly connected with the level of inequality in the city. In this context, we can interpret the correlation of Adult skills and tree canopy cover to mean that highly skilled professionals who earn more from university and tech jobs are able to choose to live in areas with more tree cover, while residents with less formal qualifications tend to live in areas with lower tree cover as they cannot afford to choose.

The connection between canopy cover and adult skills deprivation is of particular importance given the research that shows that one of the most important benefits of urban trees is the mediating effect they have on decreasing health inequality among different socio-economic groups. A systematic review looking at the existing research on urban green space and health found that most frequently demonstrated benefits that urban green spaces have on health disappeared after controlling for confounding socio-economic and socio-demographic factors (Kabisch, 2019). The strongest significance that remained after controlling for confounding factors were mental health and physical activity.

Given our significant findings in areas of social deprivation and adult skills in particular, further research looking at the equity impact of urban green space interventions in greater depth is recommended as this is still a largely under-researched area. Next steps could involve a systematic analysis of the tree interventions up to date, teasing out the most effective tools and policies and any potential mid and long-term effects urban greenspace interventions in general, or tree planting specifically, have had on social deprivation and equity.

5.1.4 Other Domains

Some domains for which a significant relationship was not found may still be influenced by the presence of trees and the canopy size. Domains such as health deprivation and outdoor living deprivation did not show a significant relationship with canopy cover in our model, yet they have been the subject of multiple studies that show positive results. We argue that the indicators used for these domains may not be suited for a direct comparison with canopy cover and propose other methods that may be better suited for the Cambridge context.

There is an increasing body of literature looking at the relationship between tree cover and human health. Some studies indicate that increased neighbourhood tree cover, independent from greenspace access, was connected to better health, predominantly in connection to lower levels of overweight and obesity and improved social cohesion, and to a lesser extent lower risk of type II diabetes, high blood pressure, and asthma (Ulmer et al., 2016). Other studies have shown an association between the amount of green space in the environment and stress levels for a deprived urban population not in work. A study in Scotland using spatial analysis and self-report measures found that the quantity and nature of access to green space were significant predictors of stress (Ward Thompson et al., 2016). In most neighbourhoods in the study, as the quantity of green space increased, the reported level of stress decreased. These results were of particular importance to urban deprived communities, where increased proximity and view to green space was a strong predictor of stress levels.

Indeed, some studies have suggested that the pathways through which canopy cover influences health are connected to the physiological responses linked to feelings of well-being inspired by direct engagement with green spaces. At the same time, it is demonstrated that green space encourages physical exercise, which is of particular importance given the rise of non-communicable diseases like type 2 diabetes. An additional pathway in which green spaces affect physiological responses are the regulating functions that they fulfil, including moderating noise, air quality and temperatures. These effects can be even more pronounced in deprived communities especially in busy, densely populated urban centres (Marselle et al., 2019).

The failure to find a relationship between tree canopy and the health decile in our regression model can be partially due to the components of the domain. The Health Deprivation and Disability Domain measures the risk of premature death and the impairment of quality of life due to poor physical or mental health (Smith et al., 2015). It is highlighted in the 2015 technical report that while the domain measures morbidity, disability and premature mortality, it does not account for aspects of behaviour or environment that may be predictive of future health deprivation (Smith et al., 2015). In this sense, the relationship between health deprivation and green space does not straightforwardly translate into the indicators. The domain is composed of indicators for 1) years of potential life lost (an age and sex standardised measure of premature death), 2) comparative illness and disability ratio (an age and sex standardised morbidity/disability ratio), 3) acute morbidity (an age and sex standardised rate of emergency admission to hospital) 4) mood and anxiety disorders (a composite based on the rate of adults suffering from mood and anxiety disorders, hospital episodes data, suicide mortality data and health benefits data). Years of potential life lost aggregates ‘premature death’ cases, which here is defined as death before the age of 75 from any cause. The causes can include death due to disease as well as external causes such as accidents, unlawful killing and deaths in combat (Smith et al., 2015). This aggregation of causes of death does not allow a connection to premature death due to air pollution, which trees have a role in preventing.

The comparative illness and disability indicator refers to work limiting morbidity and disability, based on the number of people receiving benefits due to inability to work through ill health. This indicator may not include chronic disease due to lack of or low levels of green space, such as obesity, type II diabetes, or respiratory disease, as these may not directly translate into receiving benefits due to inability to work.

The acute morbidity indicator measures the level of emergency admissions to hospital, based on administrative records of inpatient admissions, which is also not directly linked to green space.

The mood and anxiety disorders indicator measures the levels of mental ill health in the local population, and may be the indicator most straightforwardly tied to green space in the domain. It encompasses mood (affective), neurotic, stress-related and somatoform disorders and modelled on four separate sources: prescribing data, hospital episodes data, suicide mortality data, and health benefits data. However, as the indicator is based on prescription data, it may not encompass all the benefits on mental health that research has connected to increased tree canopy specifically, and green space more broadly.

In the literature looking at the relationship between health and canopy cover, some of the most consistent correlations have been identified for the association between urban green space and mental health, in particular for children and adolescents (Hunter, Cleary & Braubach, 2019). As discussed above, this dimension alone would not be readily extrapolated from the health deprivation domain alone. Further research could potentially look at the relationship between canopy cover and mental health across different age groups, and control for socio-economic and demographic factors to clarify whether canopy cover in Cambridge contributes to improved mental health outcomes as supported by the existing literature.

It has been observed that objectively measured health is the most reliable research tool because it can be less biased by indirect indicators or perceptions (Kabisch, 2019). In an applied sense, a correlation between tree canopy and health can be assessed in studies that use objective measures to assess potential links between stress levels and urban green space, e.g. through cortisol levels or electroencephalography (Kabisch, 2019). In the Cambridge context, further research could tease out some objective measures of health that are specifically related to tree canopy cover and test them across different levels of canopy cover in the city.

A mixed-method approach that systematically incorporates quantitative and qualitative methods, but also correlational and experimental methods may offer a more robust analysis of the pathways of influence between canopy cover and health.

The Living Environment Deprivation Domain measures the quality of the local environment. The indicators fall into two sub-domains. The ‘indoors’ living environment measures the quality of housing; while the ‘outdoors’ living environment contains measures of air quality and road traffic accidents. While the outdoors sub-domain may include some of the effects of the tree canopy in the ‘air quality’ indicator, the second indicator referring to road accidents could alter the correlation. Further research could potentially look at the correlation between canopy cover and air quality alone.

An increasing body of work from cities of different sizes attempt to place a value on the benefits that urban dwellers derive from the ecosystem services that trees provide in places where people live, work, play, and gather. Many of these projects use the i-Tree Eco tool to value ecosystem services provided by urban trees such as pollutant interception and carbon uptake and obtain a detailed snapshot of the structural characteristics of the tree canopy (USDA Forest Service, et al, 2006). i-Tree Eco uses standardised field data from randomly located plots across the study area and then correlates it with local hourly pollution and meteorological data. The result is a snap shot picture of the ecosystem services provided by trees and shrubs within the study area. An i-Tree Eco survey conducted in London in 2015 showed that the tree canopy in the inner London area removed approximately 288 tonnes of Nitrogen dioxide (NO_2), valued at £28,433,674.00, 105 tonnes of PM_{10}, valued £28,588,993.00, and 86 tonnes O_3 valued at £564,111.00 per year, calculated in social damage cost (UKSDC) method (Rogers et al., 2015). The value of trees for air pollutant removal is due to increase with the increase in public transport and its subsequent emissions. i-Tree can also help value the carbon sequestration benefits that trees provide in the urban setting. In the greater London area, trees store about 2,367,000 tonnes of carbon, which is valued at £147 million. Stormwater runoff retention was also valued as part of this study, at £1,191,821 per year(Rogers et al., 2015). This is also due to increase, as climate change can potentially worsen the weather conditions and put more pressure on the city sewage systems. Valuing other ecosystem services such as increasing and maintaining biodiversity could increase the value placed on urban trees. A tool that specifically values the benefits that trees offer in terms of air and water pollution would offer a more clear-cut method to assess the effects of the tree cover on the living environment.

5.2 Hedonic Pricing Discussion

The results of our hedonic regression model indicate that there is a significant positive correlation between canopy cover and property sale price between 1995 and 2008. This means that house buyers in Cambridge are willing to pay more for an increase in local tree cover. The ONS estimated that green and blue spaces contribute £4,813 to a UK average house price of £246,010(Anderson, 2018). As the average house price in our study was £271,188, the value placed on trees in particular is expected to be higher. We controlled for skewness of the data and collinearity between the valuables in this mode. The ONS calculated a predicted increase of 0.5% in house price with the presence of a small functional green space (FGS) within 200 m from the property, and a 1.5% increase for a very large FGS (Anderson, 2018).The green and blue spaces in this national study included open spaces such as parks, gardens, playing fields and sports, and other natural spaces accessible to the public. Within these estimates, the coefficient for tree cover in our model was higher than expected, indicating a 1.15% increase in house price. This could be due to a difference in valuation. Since the aggregation of different blue and greenspaces that are valued differently would produce an average price for all of them, the value of trees alone may be higher than that average. Secondly, the model that we use here does not differentiate between public and private trees, or between different distances to the treed area; we infer the tree cover in the area near the house from the tree cover proportion ascribed to the LSOA. This means that the different effects of tree cover are aggregated into a single coefficient. Therefore, we can expect trees in Cambridge to be valued higher than the national average value property owners place on greenspace, but based on existing research, we have reasons to believe that the coefficient in our model may hide different effects related to distance and quality of the trees.

The fact that number of bedrooms showed no significant correlation with house price for the 1995-2008 period has been encountered in previous hedonic pricing studies (Dimke, K. C., 2008). One explanation could be that an increase in the number of bedrooms with the floor size remaining the same would mean that the size of the bedrooms would become smaller. It is also argued in other research that as the number of bedrooms increases, the value an additional bedroom would add to the house would go down

The log-linear model that we used for 1995-2008 data gave a R^2 value of 0.57 for the 2009-2019 data. This means that the model is not as good at predicting house price after 2008. Our model shows that house buyers valued the tree cover within a 31ha are around their houses less after 2008. The model for the most recent time interval showed no significant correlation between tree cover and house price. This represents a sudden change from the 1995-2008 highly significant positive correlation. At the same time, the significance indicators for postcodes CB2 and CB3 increased compared to the first model. The positive correlation between house price and CB2 postcode area can be explained by the fact that records show CB2 to have the highest average income per household in the city. This can mean that home buyers are now willing to pay more to live in these areas in the city. The significance indicators for plot size and floor area remained at similar levels, while characteristics such as number of bedrooms, age of the building, and month of the year became significant in the second model. The type of house variables maintained their significance indicators.

The bedroom number variable changed from a no significant correlation to a significant negative correlation. This could mean that house buyers changed preferences in favour of houses with fewer rooms and more floor space. The age of the building showed a significant positive correlation in our second model. This could be due to some characteristics of older houses, such as larger floor areas, or other house features (e.g. height, windows, views, mature trees in the garden etc.) that were not included in this model. The differences in significance levels in our variables could be due to the difference in sample sizes and data treatments between the two models.

5.3 Hedonic pricing limitations

The two hedonic regression models in this paper have a number of limitations:

i. Collinearity between the independent variables is a frequent issue in hedonic analysis. Here it is addressed by restricting the model to a small number of variables. Where collinearity arose due to the number for dummy variables in the model, one variable was held constant at 0. We performed a VIF test in R to check for collinearity among the variables used in the model. The scores indicated inexistent correlation for plot size, age, type of building, month and tree cover, and moderate correlation for number of bedrooms, floor area, and postcodes CB1, CB2 and CB4. No further treatments of the data were necessary for these VIF scores.

ii. Linear regression assumes constant variance of the error term. One of the issues most commonly encountered in hedonic regression is heteroskedasticity. This occurs when the variance of the errors is not constant across observations and can cause the standard error of the coefficients to be biased. Using the log values of the data reduces heteroskedasticity in the regression model.

iii. Spatial auto-correlation is another frequently encountered issue in hedonic regression. It occurs when the relative outcomes of two points is related to their distance.

iv. Another challenge when using hedonics method is potential bias when choosing variables. This arises mainly because researchers can only access data on certain characteristics of the properties. The attributes that are omitted from the model may have higher explanatory power than some of the variables in the model. Some of these key variables may be related to availability and access to green space and natural amenities, which could in turn affect the relationship between tree cover and property price. Hence, the high coefficient number for tree canopy can cover a number of other variables and interactions that are not measured in this model and could not be valued separately.

v. Causality cannot be inferred from these models. While a correlation is established between higher tree canopy cover and an increase in property prices, we cannot guarantee that increasing the tree cover will result in an increase in property prices. To interpret these results causally would mean to assume that the models contain all the variables that influence both property prices and their relationship with tree cover. While the R^2 and p-values here suggest that we captured some key elements that influence house price, and that there is a strong correlation between tree canopy and house price at the time the data was collected, some interactions need to be further examined to establish a strong causal connection.

5.4 Recommendations

Some of the above limitations can constitute starting points for further research. Further research could look at the value of trees on the private property of house owners compared to trees in public spaces. Additionally, issues of access and distance to treed areas could be measured and included the study. Research elsewhere has employed a combination of field measurements and mapping techniques to measure the tree canopy on private property (Dimke, K. C., 2008; Siriwardena et al., 2016). As 77% of land area and 74.1 % of the tree canopy in Cambridge city is in private property (Wilson et al., 2013), field studies could help shed light on the differences in how people in Cambridge value trees on private property compared to trees on public property.

Further research could also look at the effects of canopy composition on house sale prices by analysing the value of individual trees, different tree sizes, and different species of trees. This valuation could potentially help the council develop more targeted approaches to tree planting in the future.

As noted in previous studies using the hedonic method (Sander, Polasky & Haight, 2010), the values calculated using this technique are only partial estimates of the value of urban tree cover. As the method focuses on the value that the owners of residential properties derive from their local tree cover, they likely only include the aesthetic and cultural values of trees. Other benefits provided by urban trees, such as carbon sequestration, air pollution reduction, reduction in stormwater runoff, and wildlife habitat provision, which can be argued to bring more benefits to the wider public, are not measured in the hedonic pricing approach. Therefore, the total economic value of urban trees may be larger than that captured in our models.

In summary, our results indicate that house owners would benefit from increased local tree cover, even if not directly on their property. Further research could analyse the relationship between proximity and access to local trees and house price.

Field measurements and more precise area characteristics can be further used in the development of a spatial econometric model, such as a spatial autoregressive (SAR) error model. Studies that used spatial statistics methods in conjunction with OLS regression were better able to adjust for heteroskedasticity and autocorrelation. Spatial regression models assume that the value of the dependent variable (house price) at each location is a function of both the explanatory variables at each location and the value of the dependent variable at nearby locations (Sander, Polasky & Haight, 2010).

More area characteristics may be required to conduct a spatial hedonic regression, such as proximity to amenities, local school quality, and transport facilities. Previous studies indicated that trees within proximity of 100m to a home would be valued higher than trees within a 250m buffer(Sander, Polasky & Haight, 2010). The tree cover can be further divided into multiple variables to assess the effects of different proximity levels on house price. Views of greenspace have been shown to be significant indicators of house price, so this can also be explored in further research. Spatial regression models can be further used to map the distribution of house price and tree canopy in the city.

CHAPTER 6: POLICY IMPLICATIONS AND CONCLUSION

This project attempted to develop a quantitative, systematic, and replicable way of assessing the social and economic benefits that urban dwellers in mid-sized cities in the UK derive from their local tree cover. Much of recent research has focused on attributing monetary value to the tree canopy in order to increase its prioritisation in decision-making. In this chapter, we review some approaches to urban tree assessments and valuation that could serve as model for future action that Cambridge city could undertake.

Conduct a community engaging research survey to calculate the total value of the benefits provided by trees to the entire urban community

An increased interest into methods to assess the effects of the urban tree cover also means that decisions are increasingly made on quantitative, scientifically-proven grounds instead of purely emotional or qualitative evidence (Moffat, 2016) . Increasingly, valuation tools are becoming more widely used because they offer a common language for the articulation of the benefits of trees, which can resonate with local community and decision makers alike (Moffat, 2016).

i-Tree evaluations are based in the concepts of natural capital and ecosystem services and use them to attribute a monetary value to the tree stock and the individual services it provides.

An i-Tree survey carried out in Southampton in 2017 showed an amenity value of the urban forest of £3,215 million for its 18.5% tree cover. The benefits reaped at city level from the tree canopy was in total £1.29 million per year. This included only the benefits that could be measured and valued annually, namely net carbon sequestration, air pollution removal, and avoided water runoff (Mutch et al., 2017). Additionally, the trees with the highest mean amenity value were in the most deprived areas of the city, while the least deprived areas had the highest total value of amenity trees (lowest IMD)(Mutch et al., 2017). This means that individual trees were valued more in the most deprived areas, while the total tree cover in the least deprived areas was valued higher.

While the i-Tree analysis may not capture all the benefits derived from the urban tree cover, it provides a robust benchmark for benefit assessment, and, coupled with our analysis, could help value the benefits that accrue to the people living in Cambridge: individuals, land owners, and decision-makers alike. For the UK, the i-Tree Eco tool monetises the carbon sequestration benefit by multiplying the number of tonnes of carbon stored by number of the non-traded price of carbon, since this carbon is not part of the EU carbon trading scheme(Rogers, Jaluzot & Neilan, 2012). The non-traded price is calculated based on the cost of not emitting the tonne of carbon elsewhere in the UK in order to remain compliant with the Climate Change Act (DECC 2009)(Rogers, Jaluzot & Neilan, 2012). Carbon and air pollution removal were calculated under the assumption that the benefit to society from a tonne of gas removed was equal to the cost to society of a tonne of the same gas emitted(Rogers, Jaluzot

& Neilan, 2012). For Southampton, the costs associated with pollution removal were calculated at £85,149 per year. Given that the proportion of tree cover is close to that in Cambridge, these values might be close to what would expect to find for Cambridge.

In view of the significant correlation that this project found between tree canopy and the IMD, Crime, and Adults Skills and Training domains, it can be inferred that trees in Cambridge can be considered as part of wider social development projects. Valuing the benefits that the tree cover brings to the city as a whole in terms of air pollution, water runoff, and carbon capture and storage could help build a stronger case for their importance to city residents. We recommend further assessment approaches based in contingent valuation methods to complement our hedonic pricing results and calculate the value of the benefits that the city as a whole derives from the tree cover.

At the same time, public consultation responses showed that there is support for partnerships with community groups and voluntary associations to promote tree planting. To this end, we suggest engaging community groups across different socio-economic backgrounds in valuing the benefits of their local trees. Citizen science can be used in context in conjunction with valuation tools such as iTree to increase awareness of the value of trees and produce reliable valuations of the benefits of trees at a citywide scale. The world's largest citizen science experiment was conducted in London using the i-Tree Eco tool, engaging and training over 200 volunteers for the study. (Rogers et al., 2015). This approach could serve to both obtain a monetary valuation of the ecosystem services that trees provide, and engage and educate local people in valuation techniques and the benefits of trees.

Engage land owners and encourage them to maintain and enhance the trees on their property

One emerging approach highlighted in literature is to link arboricultural projects to issues of central importance to urban dwellers and their representatives, or to national legislation (Moffat, 2016). A review of international greenspace-based interventions found strong evidence for interventions using a dual-approach, defined as physical changes to the urban green space coupled with active promotion of activities and programmes to increase residents' engagement with their local greenspaces (Hunter, Cleary & Braubach, 2019). This approach can help embed the importance of urban trees in the most pressing current or emerging challenges of the city in a more systematic way and bring more funds into tree maintenance, enhancement, and planting. As stated in the 10-year tree management strategy, the Council seeks to connect tree management and planting actions with the wider public and establish partnerships with other institutions and land owners to contribute towards increasing the tree cover (Cambridge). The results from the hedonic model in this study indicate that a monetary argument can now be made with private developers to restore and maintain the trees on their properties. As illustrated above, our most reliable dataset indicates that a 1% increase in tree cover near a property is correlated with a 1.4% increase in house price for the 2008 tree cover and house data. At the same time, mature trees have been shown to be valued more than newer trees (Siriwardena et al., 2016). This would mean that property developers would have a financial incentive to maintain the existing trees on land earmarked for development, given that house buyers would want to pay more for the trees in their area.

By means of conclusion, this project has identified the following issues:

- We have found that an increase in tree cover is correlated with improved outcomes in social deprivation, crime rate, and adult skills and training in Cambridge. Further research could look more closely at the pathways that determine these connections.
- More research is needed into the relationship between tree cover and health. More narrow indicators of health can be used, or more physical measurements of stress could be taken to compare the effects of trees across different levels of deprivation, tree cover, and demographic structure.

- Future tree interventions should take into account the connections between social deprivation and tree cover and engage communities of different deprivation status into tree valuation and learning activities.
- The hedonic model for years 1995-2008 indicated a significant positive correlation between tree cover and house price. The model could be replicated with more recent tree data for the years 2009-2019.
- Spatial hedonic regression can be conducted to improve the accuracy of the results. It should be designed to include variables for distance to the tree cover, the state of the tree canopy, and views from the house.
- Our limited, but significant results can be used to build an economic case with land developers for preservation and enhancement of existing trees on privately-owned developing sites.

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APPENDICES

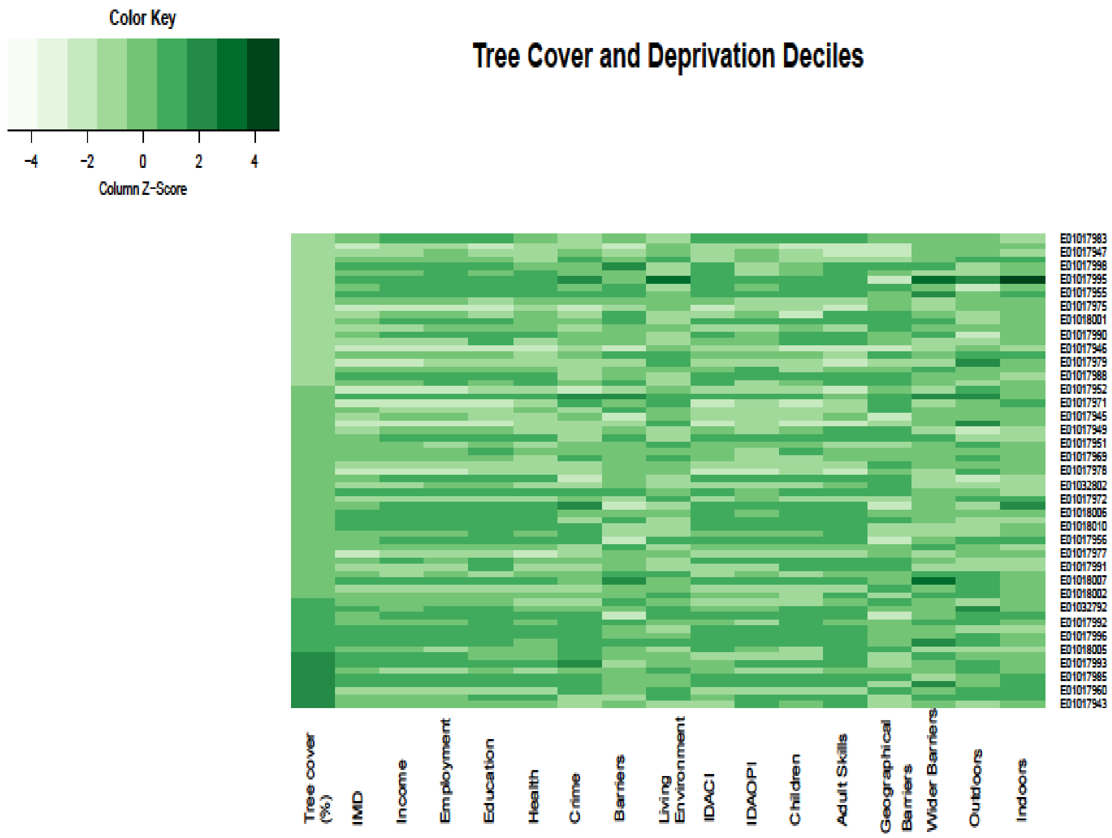

Figure 14: Heatmap of tree canopy and IMD deciles using © Bluesky International Limited tree data

	mad	min	max	range	skew	kurtosis
BD	0.00	1	7	6	0.66	1.93
FLOORSP	462.57	269	4575	4306	1.92	7.32
PLOTSZ	179.39	29	3025	2996	4.72	31.01
AGE	56.34	0	207	207	0.64	-0.36
SY	2.97	1995	2008	13	-1.29	1.15
S	0.00	0	1	1	0.90	-1.19
D	0.00	0	1	1	2.59	4.72
T	0.00	0	1	1	-0.42	-1.83
CB1	0.00	0	1	1	0.21	-1.96
CB2	0.00	0	1	1	2.06	2.23
CB3	0.00	0	1	1	4.18	15.52
CB4	0.00	0	1	1	1.03	-0.95
CB5	0.00	0	1	1	2.84	6.07
P	107495.91	37500	2256522	2219022	4.90	43.64
MONTH	2.97	1	12	11	-0.48	-0.84
TC	2.97	7	31	24	0.75	1.38

Figure 15: Skewness test for 1995-2008 house sale data

	mad	min	max	range	skew
BD	1.48	1.00	7.00	6.00	0.72
FLOORSP	415.13	269.00	4887.00	4618.00	2.06
MONTH	4.45	1.00	12.00	11.00	-0.01
YB	54.86	1800.00	2019.00	219.00	-0.48
SY	2.97	2009.00	2019.00	10.00	-0.32
S	0.00	0.00	1.00	1.00	0.68
D	0.00	0.00	1.00	1.00	2.11
T	0.00	0.00	1.00	1.00	-0.10
PLOTSZ	173.46	22.00	4001.00	3979.00	2.63
CB1	0.00	0.00	1.00	1.00	0.32
CB2	0.00	0.00	1.00	1.00	1.54
CB3	0.00	0.00	1.00	1.00	4.51
CB4	0.00	0.00	1.00	1.00	1.10
CB5	0.00	0.00	1.00	1.00	3.06
P	190321.36	49490.00	4731232.00	4681742.00	3.11
AGE	56.34	0.00	215.00	215.00	0.49
TC	4.45	7.00	31.00	24.00	0.27

Figure 16: Skewness test for 2009-2019 house sale data