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Article

Urban green space and obesity in older adults: Evidence from Ireland

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ABSTRACT

We examine the association between living in an urban area with more or less green space and the probability of being obese. This work involves the creation of a new dataset which combines geo-coded data at the individual level from the Irish Longitudinal Study on Ageing with green space data from the European Urban Atlas 2012. We find evidence suggestive of a u-shaped relationship between green space in urban areas and obesity; those living in areas with the lowest and highest shares of green space within a 1.6 km buffer zone have a higher probability of being classified as obese (BMI $\geqslant$ 30). The unexpected result that persons in areas with both the lowest and highest shares of green space have a higher probability of being obese than those in areas with intermediate shares, suggests that other characteristics of urban areas may be mediating this relationship.

1. Introduction

Over half of the world's population (54%) currently lives in urban areas (UN, 2015). Growing urbanisation is set to continue with a projected two-thirds of the global population expected to reside in urban areas by 2050 (UN, 2015). Given the worldwide trend of urbanisation, there has been renewed focus on the physical health impacts of living within these urban areas, and in particular the importance of ensuring adequate green space provision. Indeed the United Nations Sustainable Development Goal 11.7 states a target of providing "…universal access to safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities" by 2030. The benefits arising from green spaces can be examined from a multitude of angles e.g. mitigation of the urban heat island effect, promotion of local ecosystems, improved air quality and, health and wellbeing effects (see Carlin, Cormican, and Gormally (2016) for full review). This paper focuses on the physical health benefits of green space; in particular whether the presence of green space in urban areas has the potential to reduce an individual's probability of being obese.

The WHO estimates that the prevalence of obesity has more than doubled worldwide between 1980 and 2014 (WHO, 2016), with 1.9 billion adults classified as overweight in 2014, and of these, 600 million classified as obese. This is particularly concerning given that obesity substantially increases the risk of developing other noncommunicable diseases such as cardiovascular disease, diabetes, osteoarthritis and some cancers (WHO, 2016). The primary cause of obesity is an energy imbalance between calories consumed and calories expended (WHO, 2016). This imbalance is the result of increased consumption of high-energy foods and decreased physical activity. Obesity can therefore be considered a side effect of increased urbanisation, which has led to a rise in sedentary life-style patterns. Coined by Swinburn, Egger, and Raza (1999), the term obesogenic environment refers to "the sum of influences that the surroundings, opportunities, or conditions of life have on promoting obesity in individuals or populations". This definition which recognises the importance of an individual's social, economic and physical environment, shifts the focus of solving the obesity epidemic from the individual to the systemic level.

As identified by Mackenbach et al. (2014), several features of the physical environment are proposed to impact obesity including urban sprawl, land-use mix, food environment, crime rate, walkability, and green space. The primary channel through which urban green space is proposed to impact obesity is through increased physical activity. However, as identified by Lachowycz and Jones (2011) who performed a systematic review of the pre-existing literature, there is a large amount of conflicting evidence regarding the association between obesity and urban green space. In particular self-selection effects can be difficult to control for due to data limitations (Boone-Heinonen, Gordon-Larsen, Guilkey, Jacobs, and Popkin, 2011). Additional concerns arise from the use of self-reported rather than objective obesity measures, the use of observations at the geographical or population level rather than the individual level, the quality of the green space data used, and lastly, the ability to control for potentially confounding variables.

This paper attempts to overcome some of these challenges by

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linking data on individuals in The Irish Longitudinal Study on Ageing with their location in the Urban Atlas 2012 dataset. As such, our paper contributes to the literature by creating a richly detailed micro dataset linking objective health outcomes to the environment. This allows a large number of confounding variables to be controlled for at the individual level when estimating the relationship between the greenness of an area and the probability of being obese. In addition, the use of objectively measured BMI as out indicator of obesity represents an improvement on previous approaches which rely on self-reported obesity measures. Last we contribute to the literature by examining the impact of green spaces in urban areas on the probability of being obese in *older* people rather than the general population which is more commonly examined. In terms of using data from Ireland, we see that this is country in which the trends of increased urbanisation and obesity rates have both prevailed. Recent figures from the 2016 Census indicate that 63% of the Irish population live in urban areas, with 44% of the urban population living in the capital city, Dublin (CSO, 2017). Data from 2015 also estimates that 37% of the Irish population aged 15 and over is over-weight, with a further 23% obese (Healthy Ireland, 2015).

2. Background

2.1. Defining obesity

According to the WHO, obesity can be defined as 'a condition of abnormal or excessive fat accumulation in adipose tissue, to the extent that health may be impaired' (WHO, 2000). There are many different measures used to identify obesity in individuals including Body Mass Index, waist circumference and waist-hip ratio (see Burkhauser and Cawley (2008) for a comprehensive review). Body Mass Index (BMI) is the most commonly used index to classify obesity in individuals and is the obesity indicator under consideration as an outcome variable in this paper. BMI is measured as a person's weight in kilograms divided by the square of their height in meters (kg/m^2) with obesity classified as having a BMI value ≥ 30.

2.2. Defining greenness of locality

In order to proxy the "greenness" of a respondent's urban location we first define their local area or locality by drawing a circular buffer with a 1.6 km radius around their home. The greenness of an individual's locality is then calculated as the amount of green space within this buffer zone as a proportion of the total buffer zone area. We choose a 1.6 km radius as it has been used extensively in the literature (see Browning and Lee (2017); Hobbs et al. (2017) for full review) and assumes a maximum 20 minute walk to green space (see Teljeur, O'Dowd, Thomas, & Kelly, 2010). In addition, Browning and Lee (2017) find evidence that larger buffer sizes (up to 2000 m) are better at predicting physical health than smaller ones. It is important to note that while the radius size for these buffers was chosen with reference to previous research on accessibility in terms of straight line walking speed, we are not modelling green space accessibility. Instead we are using these buffers as a way to uniformly characterise the relative greenness of a respondent's locality. Further detail regarding the types of spaces we consider 'green', creation of the buffer zones and the data used are found in Section 3.2.

2.3. Green spaces and obesity

Lachowycz and Jones (2011) and James, Banay, Hart, and Laden (2015) both outline that although most studies primarily find in favour of the protective effects of green space, there is still mixed evidence regarding the association between green space and obesity. For example Cummins and Fagg (2012) find using a cross-sectional study in England that residency in the greenest areas is significantly associated with increases in overweight and obesity, and in addition that these outcomes are not attenuated by physical activity. However, using data from Canada, Prince et al. (2011) find a gender difference in the relationship, with higher green space associated with reduced physical activity levels and increased overweight/obesity in men, and decreased overweight/obesity in women.

More specifically Broekhuizen, de Vries, and Pierik (2013) perform a systemic review of the existing literature of the health effects of green space exposure in *older* people. They find evidence of a positive association between green space and physical activity, and between green space and (perceived) health, including morbidity, mortality and survival among older adults, yet conclude that there is no relationship between green space and BMI outcomes in older adults. However, this conclusion can be criticised for its over-reliance on a single paper by Li et al. (2008). Similarly, Astell-Burt, Feng, and Kolt (2014) find, using a study on Australian adults aged 45 years and older, that although green space was associated with increased moderate-to-vigorous physical activity levels and reduced sedentary behaviour, only women were found to have a reduced risk of being overweight or obese, with no protective effect found for men. Finally, Sander, Ghosh, and Hodson (2017) find that greenspace is not related to BMI for men over 50 and men and women over 65 years.

A significant difficulty with the literature is the inability to account for individuals with lower obesity outcomes self-selecting into areas which have a greater share of green space. Although the structure of our data does not allow us to completely remove this self-selection effect, we attempt to minimise it by drawing upon the literature and including a wide array of demographic and socio-economic characteristics which could simultaneously determine both the location of an individual's residence and their obesity outcome measurement. The following variables are included as confounding factors in our models: income and education (Madden, 2010), employment status (Mosca, 2013), gender (Sreetheran and Van Den Bosch, 2014), age (Chiu, Chang, Mau, Lee, and Liu, 2000; Villareal, Apovian, Kushner, and Klein, 2005), marital status (Wilson, 2012), urban location (Penney, Rainham, Dummer, and Kirk, 2014), and type of medical cover (Whelton et al., 2007). Last we control for smoking (Aubin, Farley, Lycett, Lahmek, and Aveyard, 2012; Courtemanche, Tchernis, and Ukert, 2016) and an indicator for the presence of a physical disability (Liou, Pi-Sunyer, and Laferrere, 2005).

3. Data

This paper combines two datasets from Ireland in order to examine the relationship between green space and obesity: The Irish Longitudinal Study on Ageing, and the European Urban Atlas 2012. Both are discussed in greater detail below.

3.1. TILDA

The Irish Longitudinal Study on Ageing (TILDA) is a nationally representative longitudinal study of people aged 50 and over in Ireland. Data from Wave 1 (W1) was collected between October 2009 - July 2011 from 8175 individuals aged 50 and over, from the 6279 households that participated in the study. Interviews were also conducted with the younger spouses and partners of TILDA participants (even if aged less than 50), leading to a total sample size of 8504. Interviews were conducted by trained interviewers in each respondent's home, and were carried out using Computer Assisted Personal Interviewing (CAPI). Participants were also given a self completed questionnaire (SCQ) with more potentially sensitive questions to fill out and return by mail. Last, W1 TILDA respondents were also invited to attend a nurse-led health assessment at either a specialised centre in Dublin or Cork, or a modified partial assessment in their home where travel was not practicable.

3.1.1. Outcome variable: obesity proxy

As indicated in Section 2.1, obesity can be measured in many different types of ways. This paper uses objective BMI values as our indicator of obesity. TILDA respondents who chose to participate in the health assessment (n = 5856) had their height and weight measured by a research nurse (Leahy, Nolan, O'Connell, and Kenny, 2014). An objective measure of height was recorded in centimetres using a Seca 240 wall mounted measuring rod. Similarly weight was objectively measured in kilograms using a SECA electronic floor scales (Barrett et al., 2011). In both cases the TILDA respondent was asked to remove footwear, heavy outer garments and head-wear, prior to the measurements being taken. These two measurements of height and weight were then used to calculate the BMI of each TILDA respondent.

3.1.2. Confounders

The availability of richly detailed information at the individual level in the TILDA dataset allows us to control for a large number of heterogeneous characteristics which could jointly determine both an individual's BMI measurement and the level of greenness in their surrounding area. As shown in Table 3 the following socio-economic characteristics are included in the model: age (50-64, 65-74, 75+), regional location (capital city region/other), gender (male/female), income category, marital status (married/never married/separated or divorced/widowed), employment status (employed/retired/other), education level (primary/secondary/tertiary) and type of medical coverage (none/private medical insurance/medical card[1]). Two health variables are also included as confounding variables: smoking status (never/past/current smoker) and a dummy variable equal to one if the respondent has difficulty walking 100 meters due to a physical or mental health problem.

3.2. Urban Atlas 2012: green spaces spatial data

A significant advantage of using the TILDA dataset arises from the sampling frame employed to choose the final sample (Kenny et al., 2010). The sampling frame used was the RANSAM system developed by Whelan (1979) and is based on the An Post GeoDirectory which contains geocodes for all the addresses in Ireland. This ensures that the geocode of each TILDA participant's address is recorded which in turn allows the location of each TILDA participant to be spatially matched to other datasets. In order to calculate the "greenness" of the area surrounding a TILDA individual's residence, the European Urban Atlas 2012 (EEA, 2016) dataset was employed. Produced by the European Union (EU), the Urban Atlas 2012 (UA) uses satellite imagery to create a highly detailed land-use map[2] of urban areas within the EU. In relation to the Republic of Ireland, the UA produces land-use maps which are roughly based on its five cities: Dublin,Waterford, Cork, Limerick and Galway.

In order to define our urban respondents, we employ the administrative county boundaries from the Central Statistics Office (CSO) 2011 Census. Four county boundaries are used to denote Dublin (Dublin City, Fingal, South Dublin, Dún Laoghaire-Rathdown), with the remaining urban areas denoted by Waterford City, Cork City, Limerick City, and Galway City councils respectively. These urban areas are shown in Fig. 1. Given that we are interested in examining the impact of green spaces in urban areas on the probability of being obese we classify TILDA respondents whose location is *within* these urban areas as urban TILDA respondents, with all other TILDA respondents classified as non-urban. It is important to note, that while this paper focuses on the urban TILDA respondents, the non-urban TILDA respondents are still included in our models. This allows for an increased sample size and in addition allows us to compare the effects of living in relatively green urban area with living in an area classified as 'non-urban'.

Fig. 1. Map of the island of Ireland indicating the areas considered 'urban' for this paper.

The definition of green space within an urban area can vary considerably. The definition of green space used in this paper includes the following types of land-use categories from the Urban Atlas 2012: 'Green Urban Areas'[3] and 'Sports and Leisure Facilities'.[4] Also included were the following sub-categories which were previously classified as a single 'Agricultural + Semi-Natural + Wetland area' category in the Urban Atlas 2006 dataset: arable land (annual crops), pastures, forests, herbaceous vegetation association, open spaces with little or no vegetation and wetlands.

3.2.1. Explanatory variable: greenness of locality

To create a proxy for the greenness of a TILDA respondent's locality, a circular buffer with a radius of 1.6 km was first drawn around the location of the respondent's address in Wave 1 using QGIS v.2.16. In cases where urban TILDA respondents lived close to the administrative county boundaries of urban areas, these buffers were allowed to overlap on to the surrounding land areas outside of the boundaries. However in cases where the respondent lived close to the coast, meaning that their buffers consisted of a large area of sea, the approach was slightly

[1] Medical Cards allow people to access Family Doctor or GP services, community health services, dental services, prescription medicine costs, hospital care and a range of other benefits free of charge. During 2010 (when TILDA W1 data were collected), eligibility for a medical card was assessed on the basis of an income means test.

[2] Minimum Mapping Unit of 0.25 ha (EEA, 2016).

[3] "Public green areas for predominantly recreational use such as gardens, zoos, parks, castle parks and cemeteries. Suburban natural areas that have become and are managed as urban parks. Forests or green areas extending from the surroundings into urban areas are mapped as green urban areas when at least two sides are bordered by urban areas and structures, and traces of recreational use are visible. Not included are private gardens within housing areas, buildings within parks (such as castles or museums), patches of natural vegetation or agricultural areas enclosed by built-up areas without being managed as green urban areas." (EEA, 2016).

[4] "All sports and leisure facilities including associated land, whether public or commercially managed. This includes: golf courses, sports fields, camp grounds, leisure parks, riding grounds, racecourses, amusement parks, swimming resorts, holiday villages, allotment gardens, glider or sports airports, aerodromes without sealed runway, and marinas. Not included are private gardens within housing areas, motor racing courses within industrial zone used for test purposes, caravan parking used for commercial activities, soccer fields, etc. within e.g. military bases or within university campuses." (EEA, 2016).

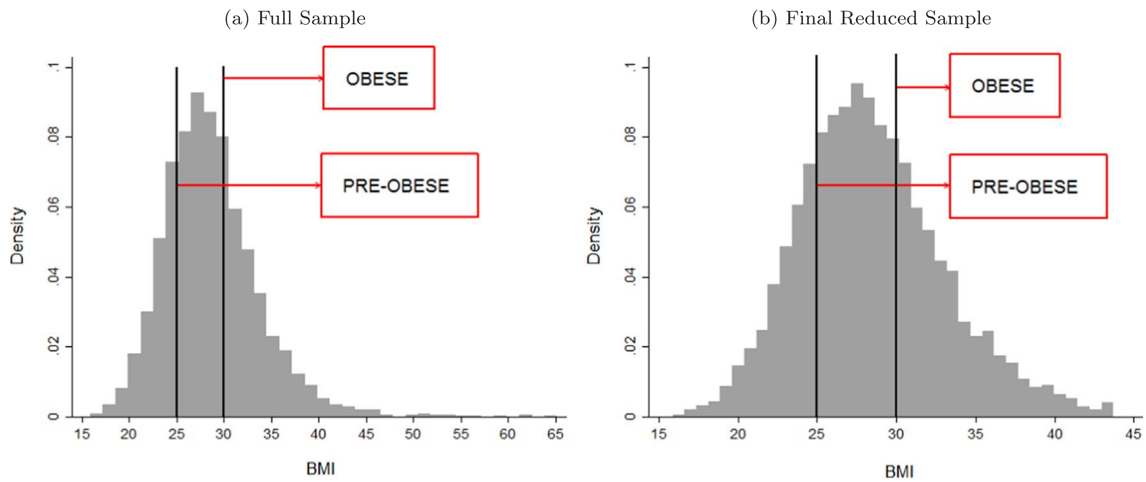

Fig. 2. Frequency Distribution of BMI with marked cut-off points for pre-obesity and obesity.

different. Here the buffers were instead truncated so as to only include those areas of land within the 1.6 km buffer zone. Having created the buffer zones for all the urban TILDA respondents within the administrative county boundaries, the area of each of these buffers was then calculated. The second step of estimating our green space proxy involved calculating the total area of green space within each of these buffer zones. This allowed the share of green space as a proportion of the total size of the buffer to be calculated. This means that the greenness of a TILDA respondent's area is estimated as the total area of green space within a buffer, divided by the total area of their respective buffer. The final green space variable for each individual is expressed in quintile form in order to protect the anonymity of the TILDA respondents, with the sixth category representing those living in non-urban areas.

4. Methodology

4.1. Descriptive statistics

4.1.1. Outcome variable

Fig. 2 illustrates the BMI distribution among our sample of TILDA respondents, in which the cut-off points for pre-obesity (BMI $\geq$ 25) and obesity (BMI $\geq$ 30) are marked. As can be seen in Fig. 2a the BMI distribution is slightly skewed to the right. In order to ensure that these BMI outliers do not drive our results, we create a sample in which we drop any observations which are three standard deviations above the mean (those with a BMI equal to 43.87 or higher). This results in 63 observations being dropped giving a total sample size of 5783 (see Fig. 5 for construction of the final sample used). In this adjusted BMI sample shown in Fig. 2b, the mean BMI value is 28.45, with the minimum and maximum value standing at 15.88 and 43.72 respectively.

Table 1 more formally describes the distribution of TILDA respondents among the different WHO classifications of obesity according to BMI, within this adjusted BMI sample. This shows that a third of our sample are considered obese, with 33.58% of the sample recording a BMI measurement $\geq$ 30. Of the remaining 'non-obese' respondents 43.37% of the total sample are classified as being pre-obese, reporting a BMI which falls between the range of $\geq$ 25 and <30. This means that in total 76.95% or TILDA respondents in our sample are considered overweight (either pre-obese or obese). Just 23.05% of the sample are classified as being a normal weight, reporting a BMI of 25 or less.[5] It is clear that Table 1 indicates that there are substantial levels of obesity within our sample of TILDA respondents, and as such, given the associated health concerns , that this is a topic which deserves further attention and research .

Table 1
Distribution of BMI classifications.

	WHO Classification	BMI	Frequency	Percent
Overweight	Obese	$\geq$ 30	1942	33.58
	Pre-Obese	<30 - $\geq$ 25	2508	43.37
Other	Normal	<25	1333	23.05
Total No Observations			5783	100

4.2. Model

Table 1 demonstrates that just under 34% of our sample are classified as obese (BMI $\geq$ 30). We therefore create a dummy variable ($obese_i$) which equals one if TILDA respondent i is obese (has a BMI value $\geq$ 30) and zero otherwise, to use as our main outcome variable of interest. Due to the discrete nature of this dummy variable, a probit model is employed to estimate the probability of being obese, given the green space category of the TILDA respondent. A probit model rather than a logit model is used as the underlying distribution of BMI looks normally distributed once the outliers are excluded, as shown in Fig. 2b. The variable $green_i$ is a categorical variable representing what quintile category TILDA respondent i falls into with regards to the share of green space in a 1.6 km radius around their residence. Last, $\mathbf{X}_{ki}$ is a matrix of individual confounding variables as discussed in Section 3.1.2. This model therefore allows us to investigate the threshold effect that green space has on the probability of a TILDA respondent being obese.

$$P(obese_i = 1, 0|green, \mathbf{X}) = \Phi(\alpha + \beta_0 green_i + \sum \beta_k \mathbf{X}_{ki}) \tag{1}$$

As a check of robustness, we employ the use of an ordered probit model which is shown in Model 2. Here the dependent variable ($bmicat_i$) is an ordered categorical variable with m indicating the BMI weight classification of each TILDA respondent. Here m is equal to one if TILDA respondent i is a normal weight (BMI <25), equal to two if TILDA respondent i is pre-obese (has a BMI $\geq$ 25 - <30) and equal to three if TILDA respondent i is obese (has a BMI $\geq$ 30). This model requires the "parallel lines assumption" in which the effect of the independent variables are assumed to be constant across the different response categories of the dependent variable, to hold.

$$P(bmicat_i = m|green, \mathbf{X}) = \Phi(\alpha + \beta_0 green_i + \sum \beta_k \mathbf{X}_{ki}) \tag{2}$$

[5] Just 0.55% of the sample were classified as 'underweight' (BMI <18.5) and were merged with the 'normal weight' category.

Table 2
Shares of 'green urban' and 'sports and leisure facilities' across quintiles.

	Q1	Q2	Q3	Q4	Q5
Green Urban	0.0632	0.0836	0.0959	0.116	0.0682
Sports and Leisure Facilities	0.0572	0.0775	0.0912	0.081	0.104

Table 3
Descriptive statistics.

Variable	Frequency	Percent
Share of urban green space in 1.6 km buffer		
1st Quintile	378	6.54
2nd Quintile	379	6.55
3rd Quintile	377	6.52
4th Quintile	381	6.59
5th Quintile	378	6.54
Non-city	3890	67.26
Regional Location		
Capital City Region	1511	26.13
Other	4272	73.87
Age Category		
50-64	3451	59.67
65-74	1540	26.63
≥ 75	792	13.7
Gender		
Male	2660	46.00
Female	3123	54.00
Income Category		
0 - 9,999	422	7.30
10,000 - 19,999	1007	17.41
20,000 - 39,999	1934	33.44
40,000 - 69,999	1236	21.37
≥ 70, 000	557	9.63
Not reported	627	10.84
Marital Status		
Married	4180	72.28
Never married	471	8.14
Separated/divorced	387	6.69
Widowed	745	12.88
Employment Status		
Employed	2205	38.13
Retired	2132	36.87
Other (coded)	1446	25.00
Smoking Status		
Never	2598	44.92
Past	2253	38.96
Current	932	16.12
Education Level		
Primary/none	1510	26.11
Secondary	2359	40.79
Third/higher	1914	33.10
Medical Cover		
Not covered	586	10.13
Medical insurance	2629	45.46
Medical card	2568	44.41
Mobility		
No difficulty walking 100 meters	5440	94.07
Difficulty walking 100 meters	343	5.93
Total	5783	100

5. Results

Table 4 presents the results from two probit models in which the outcome variable obesity is equal to one if TILDA respondent i has a BMI value ≥ 30 [6]. Model 1 in Table 4 shows a u-shaped relationship in

[6] All analysis was performed using Stata 9 (StataCorp. 2005. Stata Statistical Software: Release 9. College Station, TX: StataCorp LP.)

Table 4
Probit model examining the association between obesity (BMI ≥ 30) and urban green space.

Dependent Variable: Obese (BMI ≥ 30)	Full Model (Model 1)		Pars. Model (Model 2)	
	Coefficient	Robust Standard Error	Coefficient	Robust Standard Error
Share of urban green space in 1.6 km buffer				
3rd Quintile	[ref]	[ref]	[ref]	[ref]
1st Quintile	0.391	0.101***	0.372	0.101***
2nd Quintile	0.147	0.104	0.132	0.104
4th Quintile	0.374	0.099***	0.383	0.099***
5th Quintile	0.356	0.103***	0.352	0.103***
Non-urban	0.255	0.095***	0.349	0.077***
Regional Location				
Other	[ref]	[ref]		
Capital City Region	–0.109	0.078		
Age Category				
50 – 64	[ref]	[ref]	[ref]	[ref]
65 – 74	–0.007	0.050	[ref]	[ref]
≥ 75	−0.151	0.068**	−0.103	0.052**
Gender				
Male	[ref]	[ref]	[ref]	[ref]
Female	−0.186	0.036***	−0.206	0.035***
Income Category				
0 – 9999	[ref]	[ref]		
10,000 – 19,999	0.051	0.079		
20,000 – 39,999	0.036	0.073		
40,000 – 69,999	0.081	0.081		
≥ 70, 000	0.018	0.094		
Not reported	0.025	0.087		
Marital Status				
Married	[ref]	[ref]		
Never married	−0.057	0.068		
Separated/divorced	−0.099	0.073		
Widowed	−0.072	0.060		
Employment Status				
Employed	[ref]	[ref]	[ref]	[ref]
Retired	0.014	0.053	[ref]	[ref]
Other (coded)	0.128	0.049***	0.15	0.041***
Smoking Status				
Never	[ref]	[ref]	[ref]	[ref]
Past	0.056	0.039	[ref]	[ref]
Current	−0.243	0.053***	−0.26	0.049***
Education Level				
Secondary	[ref]	[ref]	[ref]	[ref]
Primary/none	0.129	0.045***	0.178	0.040***
Third/higher	−0.055	0.043	[ref]	[ref]
Medical Cover				
Not covered	[ref]	[ref]		
Medical insurance	−0.047	0.063		
Medical card	0.078	0.066		
Mobility				
No difficulty walking 100 meters	[ref]	[ref]	[ref]	[ref]
Difficulty walking 100 meters	0.445	0.073***	0.462	0.073***
Constant	−0.635	0.133***	−0.693	0.077***

*p <0.10.
** p <0.05.
*** p <0.01.

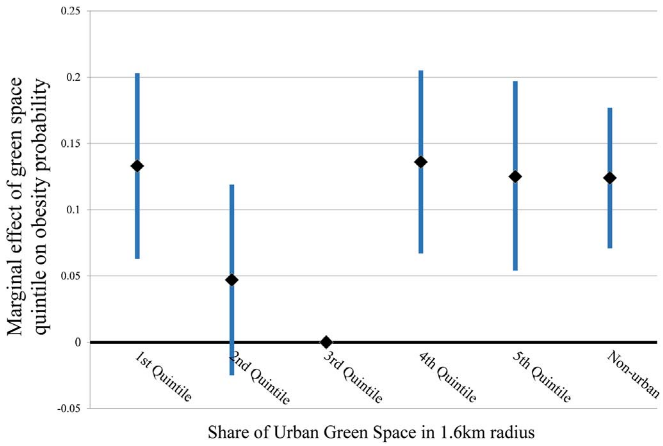

Fig. 3. Marginal effects of green space quintile (relative to 3rd quintile) on the probability of obesity. Vertical bars represent 95% confidence intervals.

which those living in areas with both the lowest and highest shares of green space in their surrounding areas have a higher probability of being obese, relative to those living in the third quintile of green space. While Model 1 controls for a large number of socio-economic and demographic characteristics of the TILDA respondent, Model 2 is a more parsimonious probit model in which variables collectively insignificant (p-value 0.18) from Model 1 are dropped. However, despite the exclusion of a large number of these confounding variables, the u-shaped relationship between the probability of being obese and share of green space in surrounding area is still found to hold, and there is little change in the green space coefficients. This suggests that our results are robust to the inclusion or exclusion of other variables.

Fig. 3 and Table 5 show the marginal effects of living in a quintile of green space relative to that of the third quintile on the probability of being obese for the parsimonious model (Model 2). Here we see that the probability of being obese is 13.3 percentage points higher for those who live in the 1st quintile of green space (with the lowest share of green space in our sample), relative to those who live in the 3rd quintile of green space. Similarly, the associated probability of being obese is 4.7 percentage points higher for TILDA respondents living in the 2nd quintile of green space, although this is not estimated to be statistically significant from those living in the 3rd quintile of green space. Interestingly, this pattern continues for those with larger shares of green space. Relative to TILDA respondents who live in the 3rd quintile of green space, those living in the 4th quintile of green space are 13.6 percentage points more likely to be obese, and those living in the 5th quintile of green space are 12.5 percentage points more likely to be obese.

As outlined in Section 2.3 previous research has indicated that the relationship between green space and obesity may differ across gender.

Table 5
Marginal effects of greenness proxy on the probability of being obese (BMI ≥ 30) relative to living in the third quintile of greenness for parsimonious model (Model 2).

	Marginal Effect	Std. Err.	z	P > z	[95% Conf.	Interval]
Share of urban green space in 1.6 km buffer						
3rd Quintile	[ref]					
1st Quintile	0.133	0.036	3.72	0.000	0.063	0.203
2nd Quintile	0.047	0.037	1.27	0.203	−0.025	0.119
4th Quintile	0.136	0.035	3.87	0.000	0.067	0.205
5th Quintile	0.125	0.037	3.43	0.001	0.054	0.197
Non-urban	0.124	0.027	4.57	0.000	0.071	0.177

Table 6
Probit model examining the association between obesity and urban green space, split by gender.

Dependent Variable: Obese (BMI ≥ 30)	Male (Model 3)		Female (Model 4)	
	Coefficient	Robust Standard Error	Coefficient	Robust Standard Error
Share of urban green space in 1.6 km buffer				
3rd Quintile	[ref]	[ref]	[ref]	[ref]
1st Quintile	0.351	0.145**	0.425	0.139***
2nd Quintile	0.092	0.143	0.215	0.145
4th Quintile	0.276	0.142*	0.470	0.138***
5th Quintile	0.301	0.142**	0.416	0.140***
Non-urban	0.183	0.133	0.315	0.134**
Regional Location				
Other	[ref]	[ref]	[ref]	[ref]
Capital City Region	−0.092	0.107	−0.135	0.105
Age Category				
50-64	[ref]	[ref]	[ref]	[ref]
65-74	0.081	0.079	−0.075	0.068
≥ 75	−0.093	0.105	−0.176	0.092*
Income Category				
0 – 9999	[ref]	[ref]	[ref]	[ref]
10,000 – 19,999	−0.082	0.118	0.151	0.102
20,000 – 39,999	−0.021	0.108	0.096	0.096
40,000 – 69,999	0.008	0.116	0.156	0.108
≥ 70, 000	0.043	0.135	−0.023	0.132
Not reported	0.029	0.128	0.042	0.112
Marital Status				
Married	[ref]	[ref]	[ref]	[ref]
Never married	0.002	0.093	−0.080	0.099
Separated/divorced	−0.016	0.121	−0.154	0.093*
Widowed	−0.086	0.103	−0.098	0.076
Employment Status				
Employed	[ref]	[ref]	[ref]	[ref]
Retired	−0.040	0.076	0.066	0.074
Other (coded)	0.178	0.089**	0.132	0.064**
Smoking Status				
Never	[ref]	[ref]	[ref]	[ref]
Past	0.108	0.056*	0.018	0.054
Current	−0.165	0.079**	−0.300	0.072***
Education Level				
Secondary	[ref]	[ref]	[ref]	[ref]
Primary/none	0.148	0.064**	0.122	0.064*
Third/higher	−0.062	0.063	−0.047	0.059
Medical Cover				
Not covered	[ref]	[ref]	[ref]	[ref]
Medical insurance	0.117	0.086	−0.198	0.090**
Medical card	0.099	0.093	0.044	0.093
Mobility				
No difficulty walking 100 meters	[ref]	[ref]	[ref]	[ref]
Difficulty walking 100 meters	0.393	0.112***	0.478	0.097***
Constant	−0.667	0.187***	−0.814	0.183***

* p <0.10.
** p <0.05.
*** p <0.01.

Models 3 and 4 in Table 6 are therefore probit models which estimate the results when the sample is split by gender. This shows that the relationship between obesity and green space still holds when estimated for each gender separately, although a more statistically significant relationship for females is evident. As another test of robustness Models 5 and 6 in Table 7 present the results from estimation of an ordered probit model (full and parsimonious model), in which the dependent variable represents the three-fold BMI classification of normal, pre-

Table 7
Ordered probit model examining association of BMI category (normal/pre-obese/obese) with urban green space.

Dependent Variable: BMI Category	Full Model (Model 5)		Pars. Model (Model 6)	
	Coefficient	Robust Standard Error	Coefficient	Robust Standard Error
Share of urban green space in 1.6 km buffer				
3rd Quintile	[ref]	[ref]	[ref]	[ref]
1st Quintile	0.272	0.084***	0.263	0.084***
2nd Quintile	0.125	0.085	0.119	0.084
4th Quintile	0.246	0.085***	0.256	0.085***
5th Quintile	0.248	0.086***	0.246	0.086***
Non-urban	0.198	0.080**	0.276	0.062***
Regional Location				
Other	[ref]	[ref]		
Capital City Region	−0.086	0.067		
Age Category				
50–64	[ref]	[ref]	[ref]	[ref]
65–74	−0.004	0.044	[ref]	[ref]
> =75	−0.178	0.060***	−0.152	0.047***
Gender				
Male	[ref]	[ref]	[ref]	[ref]
Female	−0.291	0.031***	−0.304	0.030***
Income Category				
0 – 9999	[ref]	[ref]		
10,000 – 19,999	0.028	0.068		
20,000 – 39,999	0.013	0.062		
40,000 – 69,999	0.025	0.068		
≥ 70, 000	−0.079	0.079		
Not reported	−0.042	0.075		
Marital Status				
Married	[ref]	[ref]	[ref]	[ref]
Never married	−0.133	0.060**	−0.100	0.057*
Separated/divorced	−0.082	0.062	[ref]	[ref]
Widowed	−0.049	0.051	[ref]	[ref]
Employment Status				
Employed	[ref]	[ref]	[ref]	[ref]
Retired	0.006	0.044	[ref]	[ref]
Other (coded)	0.082	0.043*	0.091	0.037**
Smoking Status				
Never	[ref]	[ref]	[ref]	[ref]
Past	0.053	0.033	[ref]	[ref]
Current	−0.308	0.046***	−0.330	0.043***
Education Level				
Secondary	[ref]	[ref]	[ref]	[ref]
Primary/none	0.116	0.040***	−0.131	0.038***
Third/higher	−0.074	0.036**	−0.224	0.041***
Medical Cover				
Not covered	[ref]	[ref]		
Medical insurance	−0.009	0.053		
Medical card	0.050	0.058		
Mobility				
No difficulty walking 100 meters	[ref]	[ref]	[ref]	[ref]
Difficulty walking 100 meters	0.414	0.070***	0.424	0.070***
Cut point 1	−0.751	0.113	−0.840	0.069
Cut point 2	0.447	0.113	0.355	0.068

* p <0.10.
** p <0.05.
*** p <0.01.

obese, and obese. Here the probability of TILDA respondent *i* moving to a higher BMI classification is estimated. Once again this demonstrates a pattern in which those living in quintiles with shares of green space both lower and higher than the share of green space in the third quintile have an increased probability of being obese.

6. Discussion: potential explanations and future extensions

As was shown in Section 5 a u-shaped relationship exists between share of green space and obesity as defined by BMI. This result partly reflects our expectation that urban respondents living in the lowest quintiles of green space would have higher levels of obesity. Unexpectedly, those living in the highest quintiles of green space were also estimated to have higher levels of obesity. These findings raise the question as to why areas with high density of green spaces do not offer the health benefits found for areas with intermediate amounts. Given that we assume physical activity is the primary channel through which green space impacts obesity, we suggest that any potential explanations will involve confounding factors affecting this transmission mechanism. Below we offer two potential explanations for why obesity levels might be found to be higher in the areas with the highest shares of green space. The first explanation relates to the literature regarding the specific attributes of green space (for example both the quality, type and size of the green space in question). However, as discussed below in Section 6.1 when controlling for both the magnitude and the type of green space in question, we find that this does not appear to offer a meaningful explanation. The second explanation relates to the availability or accessibility of green space. We argue that this explanation potentially provides a more successful avenue for future research to explore.

6.1. Characteristics of green space: type and size

We begin by first suggesting that the relationship between BMI and green space relates to specific characteristics of green space, or the green space *type* available to TILDA respondents. For example, although those on the periphery of the cities might be surrounded by green fields, these spaces may be unsuitable for engaging in physical activity. This explanation draws from Wilhelmsen, Skalleberg, Raanaas, Tveite, and Aamodt (2017), who find using cross-sectional data from Norway that increased amount of green areas within school environments increased the odds of overweight and obesity in adolescents. They argue that this due to variation in the types of green spaces available to adolescents, with rural areas consisting of croplands, forests and mountains, with urban areas tending to have more facilitated green spaces conducive to physical activity. Although our study takes place within the context of the administratively defined ‘urban areas’, many of the dwellings on the fringes of these urban centres could be quite rural in character, and as such, be suffering from this green space quality issue.

This can be more clearly seen by referring to Fig. 4 which illustrates the variation in *type* of green space, over the five quintiles measuring the share of green space in 1.6 km radius. As can be seen, the fourth and

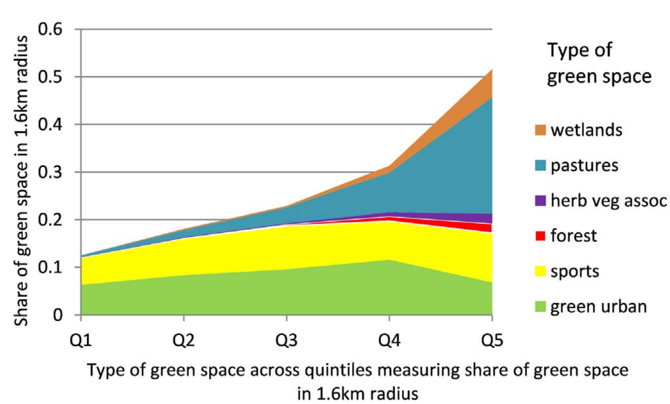

Fig. 4. Types of green space over the five quintiles measuring share of green space in a 1.6 km radius.

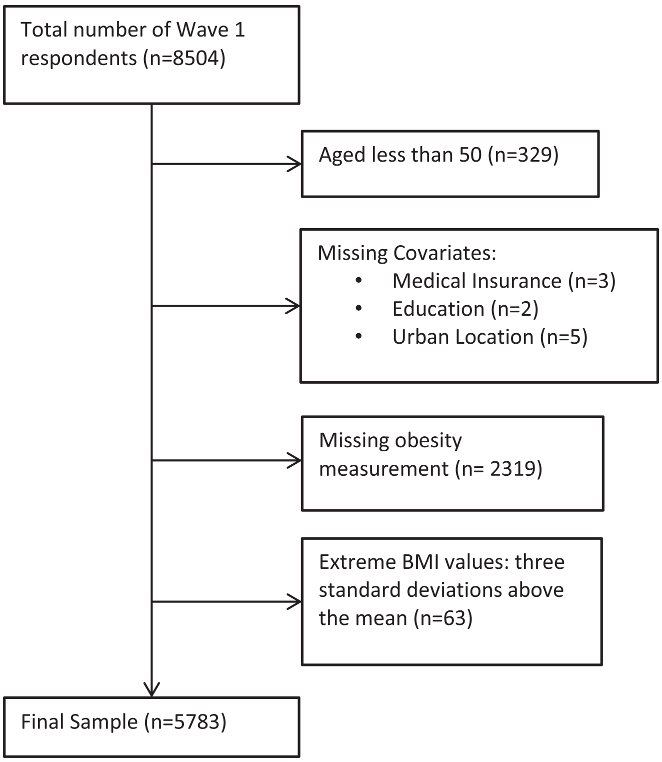

Fig. 5. Flow chart demonstrating construction of final samples.

fifth quintile register a dramatic increase in pasture land, with the fifth quintile registering an additional increase in wetlands, herbacious vegetation, forests and arable land. However while the fourth and fifth quintiles might be qualitatively different to the third quintile with regards to the types of green space available, it is clear from Fig. 4 that the first and second quintile are not qualitatively different from the third quintile on the dimension discussed here. Thus, while differentiation in the quality of green space could perhaps explain some of the u-shaped relationship over the five quintiles, it is clearly not offering a coherent framework to explain the entire u-shaped relationship. In addition, further models in which green space type was explicitly controlled for did not reveal any statistically significant relationship between green space types and BMI .

The types of green space likely to be most relevant as a facilitator of physical activity are 'green urban spaces' and 'sports and leisure facilities', which are designed with this facilitated use in mind. This brings us to the attribute of *size* of green space, which could perhaps impact on the amount of physical activity that a TILDA respondent can participate in. However, despite the increase in other types of green space, the magnitude of 'sports and leisure facilities' and 'green urban area' remains relatively constant over the five quintiles. Table 2 shows that green urban space makes up about 6% of the share of space in a 1.6 km radius for both the first and the fifth quintile, with the 2nd, 3rd, and 5th quintile showing increasing shares of green urban space at 8.3%, 9.6% and 11.6% respectively. With regards to 'sports and leisure facilities' Table 2 shows that this is a mostly positive monotonic relationship, with the share of sports and leisure facilities increasing across the five quintiles (albeit with a slight decrease in the 4th quintile). This suggests that while there is a modest u-shaped pattern for urban green space land, sports and leisure are represented by a positive monotonic relationship. In addition models which split both the 'green urban spaces' and 'sports and leisure facilities' into quintiles in order to control for the magnitude or *size* effect of green space were again found to have no statistical significance.

The findings that neither green space type nor green space size appear to offer a full explanation for the u-shaped relationship between BMI and share of green space leads us to conclude that theories which emphasise the importance of green space attributes or characteristics do not necessarily capture the full story. We therefore turn to the literature emphasising the importance of availability and accessibility.

6.2. Green space availability and accessibility

A second hypothesis for the u-shaped relationship between obesity and share of green space relates to the *availability* and *accessibility* of green spaces. In particular we suggest that these two concepts may require positive interaction in order to ensure adequate green space provision which facilitates increased physical activity. In terms of availability we roughly proxy for this by calculating the share of green space within a circular buffer zone. We argue that respondents who live in the lowest quintiles of green space are likely to be facing issues of inadequate availability of green space. However while issues of availability might help to explain why those in the lowest quintiles of green space have higher rates of obesity, it is difficult to construe how availability is an issue for those who live in the quintiles with the highest shares of green space. Here we instead suggest that the issue is the accessibility of these available green spaces.

While we proxy for accessibility by using a 1.6 km radius (estimated to be a straight-line walking distance of 20 minutes), further data might be needed to more fully control for accessibility. For example those living in areas with the highest shares of green space may lack footpaths to access, or indeed walk within these green spaces. In addition those living in the greenest areas might also have such low density that there are fewer opportunities for either recreational or routine walking, e.g. to shops. In order to test this further, information would be needed regarding the extent of the footpath (as opposed to road) network in Irish urban areas. If this hypothesis is verified, the health benefits implied from these different shares of green space could have serious implications for the development of urban planning guidelines in both urban and more rural areas. This relate to the literature regarding the contribution made by urban density/sprawl and the 'walkability' of the built environment to obesity rates (see Ellis et al., 2016; Näyhä et al., 2013; Sallis, Floyd, Rodríguez, and Saelens, 2012; Zhao and Kaestner, 2010).

While our primary explanation of accessibility relates to the footpath network, other issues of accessibility could also arise which derive from the literature on the built urban environment. These could be issues relating to the quality of the footpath network (whether paths are in good condition and have appropriate kerbs to facilitate those with decreased physical mobility), to other features of the built environment such as the presence of pedestrian lights without appropriate timings to ensure safe crossings, and street-lights. Other issues relating to green space accessibility could include the opening hours of parks, whether or not there are adequate parking facilities within the nearby facility and the location of park gates in relation to TILDA respondent homes. Furthermore, the 'Sports and Lesiure Facilties' green space type in the Urban Atlas 2012 does not distinguish between land which is publicly or commercially managed; a distinction which might be relevant in determining who can access or use the green space. Finally, it is worth noting that other issues of accessibility and subsequent usage of green space might relate to more personal emotional concepts of how vulnerable or safe older adults feel walking within these green spaces. However, without data on these variables, it is difficult to control fully the accessibility of green spaces. Future research would therefore be useful on the accessibility of existing green space, as well as the availability or characteristics of specific green spaces.

As discussed previously, the key mediator in the relationship between green space and obesity is likely to be physical activity. An investigation as to whether or not physical activity also displays a u-shaped relationship with increased share of green space might therefore help elucidate why this relationship is observed with regards to obesity. In light of this, we ran models in which the dependent variable took a value between 0 - 7 in response to the question "During the last 7 days, on how many days did you walk for at least 10 minutes at a time?". Although those who lived in the 1st quintile of green space were estimated to walk slightly more, no significant results were found in relation to the other quintiles of green space. However, this self-reported physical activity measure may be problematic as it is vulnerable to both recall and social desirability bias (for example just under 50% of our sample reported walking on all 7 days) with Prince et al. (2008) highlighting the difficulty of identifying the direction of these different biases.

7. Limitations

The main limitation of this paper relates to the extent to which share of green space in a surrounding 1.6 km radius can be considered an accurate proxy for individual green space utilisation. For example, those who live in the greenest areas may not in fact have the highest amount of green space utilisation due to issues of accessibility as outlined above. Similarly, green space utilisation might vary due to personal preferences or individual nature orientation (Lin, Fuller, Bush, Gaston, and Shanahan, 2014) which could change with advancing age (Bell, Phoenix, Lovell, and Wheeler, 2014). However, without further data capturing accessibility or personal preference, it is difficult to accurately identify the green space utilisation per TILDA respondent, and indeed how this might change according to the greenness of a respondent's locality. A second limitation of the paper relates to the potential for self-selection effects to be occurring (i.e. that people with low BMI have sorted themselves into areas with intermediate amounts of greenness for some unobserved reasons). This would mean that the observed "green effect" might be suffering from omitted variable bias, and as such, that some of the effect on obesity is being incorrectly attributed to our proxy of locality greenness. This leads to further limitation regarding the fact that we cannot attribute causality to the estimated relationship. Future research which employs panel data methods and which overcomes issues of self-selection, might allow a greater degree of causality to be claimed.

8. Conclusion

This paper contributes to the literature on green spaces and obesity by creating a dataset which combines geo-coded Irish longitudinal microdata and green space data from the European Urban Atlas 2012. In particular we add to the relatively limited pre-existing literature by employing objective rather than self-reported measures of obesity. We find suggestive evidence in favour of a u-shaped relationship between green spaces in urban areas and obesity when measured in terms of BMI. Those who have the lowest and highest shares of green space in their surrounding area have a higher probability of being obese. While we cannot be confident in assigning causality in this relationship, we control for a wide range of characteristics at the individual level which allows us to substantially attenuate any omitted variable bias. While these findings confirm the importance of ensuring the availability of adequate levels of green space in high density urban areas, the unexpected result that persons in areas with both the lowest and highest shares of green space have a higher probability of being obese than those in areas with intermediate shares suggests that other characteristics of urban areas may be mediating this relationship. We conclude that future research should incorporate the accessibility of green space (e.g., the network of footpaths) in areas which are more peripheral to urban centres and thus have the highest shares of green spaces.

Conflict of interest statement

Declaration of interest: None.

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