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Show me the money! Associations between tree canopy and hospital costs in cities for cardiovascular disease events in a longitudinal cohort study of 110,134 participants

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ABSTRACT

Health benefits from urban greening are assumed to translate into reduced healthcare expenditure, yet few studies have tested this. A total of 110,134 participants in the Sax Institute's 45 and Up Study in the Australian cities of Sydney, Newcastle, or Wollongong were linked with hospital cost data for cardiovascular disease (CVD) events (e.g., acute myocardial infarctions) up to 30 June 2018. Associations between percentages of total green space, tree canopy, and open grass within 1.6 km of participants homes and annual per person measured CVD-related hospital costs were analysed using generalised linear model (GLM) with gamma density as a component of a two-part mixture model, adjusting for confounders. Overall, 26,243 participants experienced a CVD-related hospitalisation. Incidence was lower among participants with 10 % more tree canopy (OR 0.98, 95 %CI 0.96, 0.99), but not with higher total green space or open grass percentages. Total costs of hospitalisations per year were lower with 10 % more tree canopy (means ratio 0.96, 95 %CI 0.95, 0.98), but also higher with 10 % more open grass (means ratio 1.04, 95 %CI 1.02, 1.06). It was estimated that raising tree canopy cover to 30 % or more for individuals with currently less than 10 % could lead to a within-sample annual saving per person of AU$ 193 overall and AU$ 569 for those who experienced one or more CVD-related hospital admissions. This projects to an estimated annual health sector cost reduction of AU$ 19.3 million per 100,000 individuals for whom local tree canopy cover is increased from less than 10 % to 30 % or higher. In conclusion, this longitudinal study is among the first to analyse measured healthcare cost data in relation to urban green space in general, and with differentiation between major types of greenery relevant to urban planning policies in cities around the world. In sum, this study advances an increasingly important and international focus of research by reporting on the lower burden of CVD and fewer associated hospitalisations stemming from upstream investments that protect and restore urban tree canopy, which not only translates into substantial reduced costs for the health sector, but also helps to create regenerative cities and flourishing communities.

1. Introduction

Protecting and improving cardiovascular health continues to be a challenge of paramount importance globally (Roth et al., 2017). Although advances in public health and medical care are laudable in their transformative impacts on many people, these gains are being undone (Lopez and Adair, 2019) by threats beyond the reach of the health sector, such as the inequitable impacts of climate crisis (Khraishah et al., 2022; Jacobsen et al., 2022) and poor city planning (Frumkin, 2003; Münzel et al., 2021; Feng and Astell-Burt, 2022).

Studies around the world (Feng et al., 2023; Astell-Burt and Feng, 2020; Seo et al., 2019; Dalton and Jones, 2020; Chen et al., 2020; Liu et al., 2022) indicate potential for large and durable gains in cardiovascular health can be potentially made with investment to restore and conserve urban tree canopy and green spaces in cities more generally. The Domains of Pathways conceptual model (Markevych et al., 2017;

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Astell-Burt et al., 2022) indicates greening including restoration of tree canopy may improve cardiovascular health and enhancing the management of cardiovascular disease (CVD) in three ways. First, by strengthening cardiovascular health capacities through increasing physical activity, facilitating meaningful social connections, and supporting better quality sleep. Second, by restoring psychological capacities through stress relief and renewal of cognitive capacities depleted through adaptation to challenging circumstances. Third, through providing protection from ambient hazards that increase risk of CVD, such as heatwaves and air pollution. It is acknowledged that these domains of pathways are closely entwined and potential synergies can influence both the magnitude and direction of potential impacts on health.

These findings linking greening and cardiovascular health are persuasive for some, but many end-users often remark that evidence of associations with lower hospital costs could be more potent for policy impact. Their question is, if having more tree canopy nearby helps to keep people heart healthy and out of hospital, then how much money is saved from hospitalisations that did not occur?

Current evidence on greening and healthcare expenditure in cities is in a nascent period and unable to give a firm answer to this question (Patwary et al., 2023). Only a few high-quality studies have attempted to quantify health economic cost-savings of greening (Van Den Eeden et al., 2022; Astell-Burt et al., 2022) Some studies rely on methods such as projections (e.g., Wolf et al., 2015) or value of statistical life (e.g., Kondo et al., 2020) that do not analyse measured healthcare expenditure; a problem given highly constrained health systems budgets globally indicate many people who could benefit from medical treatment do not receive it. Furthermore, a recent review found many studies to be limited by ecological data with partial adjustment for person-level confounding, missing critical variables that influence healthcare use and access to or contact with green space, such as educational qualifications and income level (Patwary et al., 2023). Research specifically on green space and cardiovascular healthcare expenditure is scarce, with one study reporting higher rates of prescribing and spending on medications for treating CVD. (Gidlow et al., 2016).

In this study we attempt to provide a more robust answer to this question by utilising a longitudinal cohort study with linked green space variables and 10 years of hospital records for acute myocardial infarctions (AMI) and other CVD-related events, for which most people tend to seek urgent medical attention. This work builds on previous studies of the same data that report lower odds of CVD onset (Astell-Burt and Feng, 2020) and CVD-related hospitalisations among individuals in areas with higher tree canopy cover, after adjusting for confounding factors (Feng et al., 2023). We hypothesized that annual per person CVD-related hospital costs are lower among residents of areas with higher percentages of tree canopy cover, given the previously reported lower risk of CVD-related events necessitating hospital admissions.

2. Methods

2.1. Data and sample

The Sax Institute's 45 and Up Study baseline (n = 267,357) was recruited between 2005 and 2009 from the Services Australia enrolment database with a response of approximately 19 % (Bleicher et al., 2023; 45 and Up Study, 2008). About 11 % of the New South Wales (NSW) population 45 years and older participated and is broadly representative of the population aged 45 years and over in Australia (Johar et al., 2012). People 80 + years of age and residents of rural and remote areas were oversampled. Participants gave written informed consent for their responses to be linked to other data for research purposes including death records (the Register of Births, Marriages and Deaths, and the Cause of Death Unit Record File) and all admissions to public and private hospitals in NSW (the Admitted Patient Data Collection). Linkage of participants in the 45 and Up Study to records of hospital admissions and/or deaths between 1 July 2000 to 30 June 2018 for public and private hospitals by the Centre for Health Record Linkage (CHeReL) (http://www.cherel.org.au/). CHeReL uses a probabilistic procedure to link records, in which records with an uncertain probability of being true matches are checked by hand. Its current estimated false positive rate is 0.5 %. Ethics approval for the 45 and Up Study was awarded by the University of New South Wales Human Research Ethics Committee (HREC), while this study was approved by the NSW Population and Health Services Research Ethics Committee.

We focussed on a sample of 110,134 participants living in Sydney, Newcastle, and Wollongong, the three largest cities in NSW. Sydney is considered a 'major city' in Australia and is not only the largest of the three in our study, but also the most populous city in the country at over 5 million residents. In contrast, Newcastle and Wollongong are considered 'regional cities' with approximately 322,000 and 300,000 residents, respectively. All three cities are located on the south-east coast and are characterised by sprawling low-rise car-dependent suburbs with mainly detached housing. Wollongong is about 93 km south and Newcastle approximately 168 km north of Sydney by road. The state health department (NSW Health) is responsible for managing and funding 220 public hospitals and health services that provide free healthcare to Australian citizens and permanent residents in these cities, including emergency care, elective and emergency surgery relevant to our study.

The focus on cities was to reduce potential confounding between green space and CVD related to use of endocrine disrupting chemicals in fertilisers on farmland.(Fu et al., 2020) In this sample there were 2,704,400 hospitalisation records, which included 55,347 acute episodes related to CVD from the time of the baseline interview till June 30, 2018 by date of discharge. The focus on hospitalisations for acute CVD events was made via restrictions of omitting: (a) participants no longer active in survey, absent a principal diagnosis, negative or zero difference between time of discharge and time of admission from hospital, and identical copies (n = 3,199); (b) records with identical admission and discharge time (5,029); (c) with identical admission time only (n = 399), and (d) with identical discharge time only (n = 1,179).

2.2. Outcomes

We examined the annual per person CVD-related hospital costs, including for stroke, based on acute care type hospital admissions characterised by the National Efficient Price (NEP) from 2012 to 2013, expressed in Australian dollars ($AU) paid to hospitals by government. This approach is aligned with that used previously (Yu et al., 2017; Marashi et al., 2019). Acute care hospitalisations with a CVD principal diagnosis were defined by the International Classification of Diseases 10th revision-Australian Modification (ICD-10-AM) codes I00 to I99 (diseases of the circulatory system, including ischaemic heart diseases, hypertensive diseases, cerebrovascular diseases, pulmonary heart diseases, and chronic rheumatic heart diseases), G45 and G46 (transient cerebral ischaemic attacks and related, and vascular syndromes of brain in cerebrovascular diseases, respectively). The cost of these and other hospital admissions is defined by the Independent Hospital Pricing Authority (IHPA) in Australia. IHPA develops the National Efficient Price (NEP) for the National Weighted Activity Unit (NWAU) and the means for calculating the NWAU for a given time (Independent Hospital Pricing Authority (IHPA), 2013). The NEP per NWAU for 2012–13 was set at $AU 4,808. The NWAU for an admission is defined mainly on the Australian Refined Diagnosis Related Groups (AR-DRGs) classification, which is a clinically meaningful category assigned to a record based on combination of diagnoses and procedures with similar resource allocations, in addition to 15 other variables. The most important of the other 15 variables affecting the NWAU is length of stay (LOS) of a patient, and its relation to a normative LOS. LOS is calculated as day of discharge minus day of admission minus any leave days from hospital. Same-day admissions are assigned with an LOS equal to 1. Others, such as location, source of funding, stay in intensive care unit also adjust the NWAU.

A particular NWAU multiplied by NEP gives the cost of admission. Records in our data were grouped under AR-DRG v6.0, while the first pricing model for 2012–13 used the extended version of this classification, AR-DRG v6.0x; cardiovascular DRGs are not affected by the differences in these versions. An Excel-based macro developed by IHPA was used to determine NWAU and cost for admissions (Independent Hospital Pricing Authority (IHPA), 2013;IHPA, 2013). All hospital admissions for CVD events were included in the calculation of the outcome regardless of their funding source (i.e., public or private hospitals). In addition to annual per person CVD-related hospital costs, we also examined the per person mean cost per CVD-related hospital admission per year and the per person count of CVD-related hospital admissions per year, to examine whether potential associations with green space variables are driven by differences in hospital admission frequency, or variations in the cost per admission.

2.3. Green space variables

Best available two-metre high-resolution land-use data (sourced from Pitney Bowes Ltd) was used to ascertain the total percentage of all green space available within a 1.6 km (1 mile) road-network buffer calculated around proxy locations of residence at baseline (Mesh Blocks, containing between 30 and 60 dwellings each). A 1.6 km buffer size reflects a reasonable walking distance to define cumulative opportunities for benefiting from local green spaces. We then calculated the percentage tree canopy cover and open grass within the same road-network buffers, as previous research has reported contrasting degrees of association between different types of green space and some health outcomes (Nguyen et al., 2021) including for CVD onset (Astell-Burt and Feng, 2020) and hospitalisations (Feng et al., 2023). Tree canopy included all deciduous and evergreen trees on public and private land. Open grass was defined by low level vegetation unobstructed by tree canopy, such as gardens, sports ovals, and large grassy reserves.

2.4. Potential confounders

Common causes of contact with green space and the risk of CVD events include socioeconomic and demographic factors. Accordingly, we controlled for differences in sex, age, couple status, annual household income ($AU before taxation), highest educational qualification, and work status (see Supplementary Table S6 for details).

2.5. Statistical analysis

Analysis was performed using SAS Enterprise Guide software (Version 8.4). Raw data were described using frequencies, means and standard errors. SAS Finite Mixture Models procedure was used to fit three types of two-part mixture models (SAS Institute Inc, 2015; Kessler and McDowell, 2012) allowing for excess of zeros in the data. The first component of the models was represented by constant density with value zero. The second component gave rise to three "Types" of models for each of the previously described outcome variables, fitted on subset of data with outcomes > 0. These are as follows:

(1) Annual per person CVD-related hospital costs were analysed using generalised linear model (GLM) with gamma density. The interpretation of exponentiated regression coefficients (except for intercept) is the mean of total cost ratio;
(2) Per person mean cost of CVD-related hospital admission was also defined by GLM with gamma density. It had a similar interpretation, i.e., mean of admission cost ratio;
(3) Annual per person count of CVD-related hospital admissions was modelled by (3a) GLM with zero-truncated negative binomial density, where exponentiated coefficients refer to the rate of admission per year ratio. However, to predict not on count scale, but on number of admissions per year, a (3b) GLM model with gamma density was fitted.

Common to these types of the models was a "Type 0", which is a logistic regression estimating the mixing probability of a hospital admission over the period of observation for the models of Type 1 to 3. Model is fitted by SAS on full sample using internal indicator variables, coded 1/0 for cases of outcome > 0/=0. All models are fitted independently and separately. For predictions on full sample, the predicted value obtained from Type 1, 2 or 3 models is multiplied by the predicted probability of outcome being > 0 obtained from Type 0 model. The details of a typical SAS code are in Supplementary Table S7. Models were developed for each green space variable separately and as linear (i.e., continuous) terms adjusted for confounders. A number of sensitivity tests were then conducted. First, we investigated whether results for tree canopy and open grass variables when fitted simultaneously were like those results when examined separately. The green space variables were then assessed as intervals to check for potential non-linearities of association with the outcomes. Further sensitivity tests were conducted to assess for impacts made by the period of observation and occurence of death across the green space variables, with 16,846 (15.3 %) deaths among the 45 and Up Study baseline participants up to 30 June 2018.

2.6. Prediction methods

The aim of predictions was to compare associations for participants with tree canopy comprising less than 10 % of local land-use versus 30 % or higher. The comparison was performed on raw data and on predictions for each participant generated by using Model types 1, 2 and 3b. Three methods were used for the prediction: models with tree canopy formatted as a continuous variable (Method 1), models with a categorical version of the tree canopy variable, contrasting less than 10 % to ≥ 40 % with a 10 % step (Method 2) and models with a categorical tree canopy variable contrasting less than 10 % to ≥ 30 % with a 10 % step (Method 3). In case of raw data and Methods 1–2, the differences between areas less than 10 % and ≥ 30 % were derived from means and variances of participants living in the respective areas. In Method 3, the predictions were calculated from the data of participants who had less than 10 % where the value of green space were set to ≥ 30 % to approximate the outcome of a successful urban greening strategy or place-based intervention. Predictions for mean and variance (var_i) for each individual participant were aggregated over respective trees areas assuming independence; aggregated standard deviations (SD) were derived as $sqrt(sum(var_i)/n^2)$. SD for the difference between categories were calculated as $sqrt(SD1^2 + SD2^2)$. See SAS code for obtaining predictions in Supplementary Table S7.

3. Results

A total of 26,243 out of 110,134 participants in the sample experienced a CVD-related hospital admission (Table 1). The unadjusted rate of admissions was lower among participants with more green space overall (e.g., 22.1 % for ≥ 60 % green space, compared with 23.9 % for < 20 % green space) and also for more tree canopy cover (e.g., 22.8 % for ≥ 40 % tree canopy, compared with 24.3 % for < 10 % tree canopy), but not for more open grass. Total costs of admissions per year tracked down with more green space overall (e.g., AU$ 2202 for ≥ 60 % green space, compared with AU$ 3062 for < 20 % green space) and more tree canopy (e.g., AU$ 2549 for ≥ 40 % tree canopy, compared with AU$ 3152 for < 10 % tree canopy) specifically, but not statistically significantly for more open grass. Similar patterns were observed for the mean cost per admission. Admissions per year were lower for higher levels of green space in general, but not for tree canopy and open grass when analysed separately.

Rates of admission were higher among men (29.0 %) compared with women (19.1 %), older versus younger individuals in the sample (e.g.,

Table 1
Descriptive statistics.

Variable	Full sample (N = 110,134)				Sample with at least one admissions (N = 26,243)						
Category	Occurence of participants with admission/s					1 Total cost/year		2 Mean cost/admission		3 N admissions/year	
Statistics	N total	N events	%	SE(%)	N	Mean ($AU)	SE	Mean	SE	Mean	SE
Sample size	110,134	26,243	23.8	0.13	26,243	2865	58	8466	61	0.309	0.005
Total green space %											
0–19 %	2,252	539	23.9	0.90	539	3062	384	8672	326	0.314	0.024
20–29 %	28,097	6,727	23.9	0.25	6,727	2961	127	8752	132	0.304	0.007
30–39 %	30,565	7,541	24.7	0.25	7,541	2910	123	8430	110	0.315	0.009
40–49 %	28,704	6,743	23.5	0.25	6,743	2818	94	8286	115	0.312	0.009
50–59 %	15,217	3,524	23.2	0.34	3,524	2865	149	8518	173	0.317	0.019
60 % and above	5,299	1,169	22.1	0.57	1,169	2202	119	7837	240	0.260	0.011
Statistics		χ^2 = 26.9	P ≤ 0.001	V = 0.016		KW = 17.0	P ≤ 0.01	KW = 16.7	P ≤ 0.01	KW = 16.4	P ≤ 0.01
Tree canopy %											
0–9 %	13,545	3,286	24.3	0.37	3,286	3152	265	8701	185	0.329	0.021
10–19 %	44,744	10,756	24.0	0.20	10,756	2939	88	8674	97	0.307	0.005
20–29 %	26,914	6,496	24.1	0.26	6,496	2636	72	8306	120	0.298	0.007
30–39 %	16,827	3,856	22.9	0.32	3,856	2934	160	8068	153	0.319	0.014
40 % and above	8,104	1,849	22.8	0.47	1,849	2583	152	8228	211	0.308	0.030
Statistics		χ^2 = 16.2	P ≤ 0.01	V = 0.012		KW = 18.8	P ≤ 0.001	KW = 25.5	P ≤ 0.001	KW = 6.7	
Open grass %											
0–9 %	58,217	13,881	23.8	0.18	13,881	2891	80	8383	82	0.310	0.006
10–19 %	29,055	6,923	23.8	0.25	6,923	2940	137	8610	129	0.315	0.011
20–29 %	18,228	4,391	24.1	0.32	4,391	2740	90	8520	136	0.305	0.008
30 % and above	4,634	1,048	22.6	0.61	1,048	2549	177	8375	319	0.279	0.012
Statistics		χ^2 = 4.4		V = 0.006		KW = 2.4		KW = 3.0		KW = 0.7	
Gender											
Male	52,445	15,201	29	0.20	15,201	3220	78	9157	84	0.333	0.007
Female	57,689	11,042	19.1	0.16	11,042	2377	86	7515	87	0.276	0.005
Statistics		χ^2 = 1466.7	P ≤ 0.001	V = 0.115		KW = 420.9	P ≤ 0.001	KW = 381.2	P ≤ 0.001	KW = 147.8	P ≤ 0.001
Age											
45–54 y	33,495	3,377	10.1	0.16	3,377	1385	55	7296	212	0.170	0.003
55–64 y	34,383	6,295	18.3	0.21	6,295	1785	58	7430	106	0.213	0.004
65–74 y	20,680	6,522	31.5	0.32	6,522	2754	137	8936	125	0.287	0.012
75–84 y	17,008	7,875	46.3	0.38	7,875	3866	132	9276	108	0.400	0.010
≥85 y	4,568	2,174	47.6	0.74	2,174	4996	231	8935	201	0.542	0.021
Statistics		χ^2 = 10895.3	P ≤ 0.001	V = 0.315		KW = 2813.0	P ≤ 0.001	KW = 1084.1	P ≤ 0.001	KW = 2865.3	P ≤ 0.001
Educational attainment											
None	10,717	3,470	32.4	0.45	3,470	3538	237	8893	156	0.364	0.011
School	65,716	16,403	25	0.17	16,403	2933	72	8559	77	0.313	0.007
University	31,849	5,730	18	0.22	5,730	2182	77	7869	125	0.257	0.008
Undetermined	1,852	640	34.6	1.11	640	3579	311	9104	575	0.398	0.023
Statistics		χ^2 = 1079.7	P ≤ 0.001	V = 0.100		KW = 337.5	P ≤ 0.001	KW = 134.4	P ≤ 0.001	KW = 299.6	P ≤ 0.001
Household income (AUD $)											
0-$29,999	26,878	8,983	33.4	0.29	8,983	3499	122	9080	108	0.352	0.006
$30,000-$69,999	25,788	5,708	22.1	0.26	5,708	2611	115	8207	123	0.290	0.013
≥ $70,000	32,845	5,009	15.3	0.20	5,009	1758	82	7249	133	0.222	0.013
Undetermined	24,623	6,543	26.6	0.28	6,543	3063	109	8780	125	0.334	0.009
Statistics		χ^2 = 2769.7	P ≤ 0.001	V = 0.180		KW = 974.0	P ≤ 0.001	KW = 457.9	P ≤ 0.001	KW = 815.6	P ≤ 0.001
Couple status											
Yes	80,400	18,033	22.4	0.15	18,033	2611	66	8273	71	0.286	0.006
No	29,065	8,019	27.6	0.26	8,019	3406	117	8881	119	0.359	0.009
Undetermined	669	191	28.6	1.75	191	4109	672	9230	760	0.380	0.050
Statistics		χ^2 = 313.5	P ≤ 0.001	V = 0.054		KW = 250.9	P ≤ 0.001	KW = 97.2	P ≤ 0.001	KW = 269.8	P ≤ 0.001
Work status											
Working	58,112	8,967	15.4	0.15	8,967	1806	57	7633	107	0.214	0.007
Retired	41,190	14,729	35.8	0.24	14,729	3470	92	8998	82	0.362	0.007
Unemployed	2,289	477	20.8	0.85	477	2497	244	8884	491	0.263	0.018
Sick or disabled	2,335	665	28.5	0.93	665	3947	369	8802	301	0.426	0.040
Other	6,208	1,405	22.6	0.53	1,405	2895	275	7902	208	0.325	0.024
Statistics		χ^2 = 5515.5	P ≤ 0.001	V = 0.230		KW = 1375.4	P ≤ 0.001	KW = 552.2	P ≤ 0.001	KW = 1315.5	P ≤ 0.001

Full sample was analysed for the associations related to the occurrence of at least one admission ||
Costs and number of admissions on subset of participants with at least one admission was analysed with non-parametric analysis of variance (ANOVA) in SAS Proc NPAR1WAY ||
Frequencies were calculated using SAS Proc Freq.
χ2 = Chi-Square value||V = Cramer's V for association of nominal variables|| KW = Kruskall-Wallis non-parametric Chi-Square test || p = P-value

(*continued on next page*)

Table 1 (*continued*)

Variable	Full sample (N = 110,134)				Sample with at least one admissions (N = 26,243)						
Category	Occurence of participants with admission/s					1 Total cost/year		2 Mean cost/admission		3 N admissions/year	
Statistics	N total	N events	%	SE(%)	N	Mean ($AU)	SE	Mean	SE	Mean	SE

events = a participant with hospital admission/s || SE = standard error calculated manually as a binomial error for a percent for illustration||
$AU = Australian dollars
2012–13 ||

47.6 % among 85 yr+, compared with 10.1 % for those aged 45–54 yr), those with minimal formal education attainment (32.4 %) versus university graduates (18.0 %), on lower household incomes (33.4 % for those on AU$ 0–19,999 compared with 15.3 % for those on AU$ ≥70,000 per annum), not in a couple (27.6 %) compared to those in a couple (22.4 %), and those who were retired (35.8 %) compared with those in work (15.4 %). After adjusting for these confounding factors (Table 2, Model type 0), incidence of admission was lower with 10 % more tree canopy when modelled separately (Odds Ratio [OR] 0.98, 95 % confidence interval [95 %CI] 0.96, 0.99) and after additionally accounting for open grass within the same model (OR 0.98, 95 %CI 0.96, 0.99). Incidence of admission was not associated with higher overall green space or open grass.

The adjusted total cost of admissions per year (Table 2, Model type 1) were lower with 10 % more green space overall (means ratio 0.99, 95 % CI 0.97, 1.00) and with 10 % more tree canopy specifically (means ratio 0.96, 95 %CI 0.95, 0.98), but also higher with 10 % more open grass (means ratio 1.04, 95 %CI 1.02, 1.06) when fitted separately. Similar though slightly attenuated results were found when fitting both tree canopy and open grass within the same model. The adjusted mean cost per admission (Table 2, Model type 2) was also lower for 10 % more green space and tree canopy (both means ratios 0.99, 95 %CI 0.98, 1.00). Rates of admissions per year were lower with more tree canopy and higher with more open grass in separate models only (Table 2, Model types 3a and 3b). Full results with parameters for all covariates are reported in Supplementary tables 1-5.

Assessment of potential non-linearities using intervals for each green space variable indicated consistently statistically significant associations only for total cost per year (Table 3, Model type 1) and tree canopy, before and after accounting for open grass as a covariate. For example, the means ratio for ≥ 40 % tree canopy compared with < 10 % was 0.78 (95 %CI 0.73, 0.84) in the two green space variables model. Mean cost per admission was lower for 20–29 % and 30–39 % tree canopy compared with < 10 %, but not for ≥ 40 % tree canopy, whereas rates of admission were consistently lower where tree canopy was greater than 10 % of nearby land area. Open grass was not associated with total cost per year, mean cost per admission, or the rate of admissions per year after adjusting for tree canopy.

Table 4 reports predictions from these models. We estimate that greening strategies which raise tree canopy cover to 30 % or more for individuals with currently less than 10 % could lead to a within-sample total CVD event related cost per year per person saving of AU$ 193 overall and AU$-569 for those who experienced one or more CVD-related hospital admissions. This projects to an estimated hospital cost reduction of AU$ 19.3 million per year per 100,000 individuals for whom tree canopy rose from < 10 % to at least 30 %. Sensitivity analyses in which we augmented the predictions for tree canopy as a continuous variable or top-coding the intervals to 30 % did not change the results substantively.

4. Discussion

Intuition and evidence (Markevych et al., 2017; Astell-Burt et al., 2022) indicate that contact with nature for populations living in cities is beneficial for their health and wellbeing. But considerations of urban green space as a health resource are often given a low priority by many planners and developers and attributed no priority at all by many healthcare professionals. It is felt by some commentators that demonstrations of population health gains would be more potent catalysts for positive change if they were accompanied by robust data on healthcare expenditure saved. In this study we built upon previous studies that reported lower odds of cardiometabolic disease onset and lower risks of

Table 2
Summary of three two-part mixture models for associations between green space variables (in 10% units) and hospitalisations.

		Exponentiated regression coefficients for the green space variables				
		Model type 0	Model type 1	Model type 2	Model type 3a	Model type 3b
Model No	**Green space variables**	Incidence of admission Odds ratio (95 % CI)	Total cost/year Means ratio (95 % CI)	Mean cost/admission Means ratio (95 % CI)	N admissions/year Rate ratio (95 % CI)	N admissions/year Rate ratio (95 % CI)
Single green space variable models						
1	Total green space % (%/10)	0.99 (0.98, 1.00)	0.99 (0.97, 1.00) +	0.99 (0.98, 1.00) +	0.99 (0.97, 1.01)	1.00 (0.99, 1.01)
2	Tree canopy % (%/10)	0.98 (0.96, 0.99) *	0.96 (0.95, 0.98) *	0.99 (0.98, 1.00) x	0.97 (0.95, 0.99) x	0.98 (0.97, 0.99) *
3	Open grass % (%/10)	1.01 (1.00, 1.03)	1.04 (1.02, 1.06) *	1.00 (0.99, 1.02)	1.04 (1.01, 1.08) x	1.03 (1.02, 1.05) *
Two green space variables model (trees + grass)						
4	Tree canopy % (%/10)	0.98 (0.96, 0.99) x	0.97 (0.96, 0.98) *	0.99 (0.98, 1.00) x	0.98 (0.95, 1.00)	0.99 (0.98, 1.00)
	Open grass % (%/10)	1.00 (0.98, 1.02)	1.02 (1.00, 1.04) +	1.00 (0.98, 1.01)	1.03 (1.00, 1.07)	1.03 (1.01, 1.04) *

GLM = generalised linear model || CI = confidence intervals || * P ≤ 0.001, x P ≤ 0.01, + P ≤ 0.05.
Model type 0. Incidence of any hospitalisation (Mixing probability logistic model common to Models 1 to 3), built on the whole set.
Model type 1. Total cost per year (GLM with gamma density).
Model type 2. Mean cost of a hospitalisation per admission (GLM with gamma density).
Model type 3a. Rate of hospitalisations per year (GLM with zero-truncated negative binomial density with offsets).
Model type 3b. Rate of hospitalisations per year (GLM with gamma density).
Model types 1 to 3b are conditional on the occurrence of admission; with respect to regression coefficients are built on a subset of participants with an admission.
Modelling is done using SAS Proc FMM maximum likelihood algorithm || Second component of the models is constant zero density.
Models are fitted with adjustment for all co-variates: gender, age, education, income, working and marital status.
Green space continuous variables are expressed in 10% units; exponentiated coefficients are related to 10% increase in green space.
N total = 110,134; N participants with any CVD hospitalisation = 26,243 (23.8 %);
Observation period is from baseline interview till June 30, 2018 (9.6 ± 2.1 years; Mean, Standard deviation.

Table 3
Summary of three two-part mixture models of association between green space intervals and CVD-related hospitalisations.

		Exponentiated regression coefficients for the green space variables				
		Model type 0	Model type 1	Model type 2	Model type 3a	Model type 3b
Model No	**Green space variables**	Incidence of admission Odds ratio (95 % CI)	Total cost/year Means ratio (95 % CI)	Mean cost/admission Means ratio (95 % CI)	N admissions/year Rate ratio (95 % CI)	N admissions/year Rate ratio (95 % CI)
Single green space variable models						
1	**Total green space % (ref = 0–19 %)**					
	20–29 %	0.99 (0.89, 1.10)	0.99 (0.90, 1.10)	1.02 (0.95, 1.10)	0.94 (0.79, 1.12)	0.97 (0.90, 1.04)
	30–39 %	0.99 (0.89, 1.10)	1.00 (0.91, 1.11)	0.99 (0.92, 1.06)	0.95 (0.80, 1.13)	1.00 (0.93, 1.08)
	40–49 %	0.98 (0.88, 1.09)	1.00 (0.90, 1.10)	0.98 (0.92, 1.05)	0.98 (0.82, 1.16)	1.02 (0.95, 1.10)
	50–59 %	0.96 (0.86, 1.07)	0.99 (0.90, 1.10)	1.01 (0.94, 1.08)	0.98 (0.82, 1.17)	1.02 (0.95, 1.10)
	60 % and above	0.94 (0.83, 1.06)	0.84 (0.75, 0.94) x	0.95 (0.88, 1.03)	0.81 (0.66, 0.99) +	0.87 (0.80, 0.95) x
2	**Tree canopy % (ref = 0–9 %)**					
	10–19 %	0.97 (0.92, 1.02)	0.87 (0.83, 0.91) *	1.00 (0.97, 1.03)	0.90 (0.84, 0.98) +	0.88 (0.86, 0.91) *
	20–29 %	0.94 (0.89, 0.99) +	0.79 (0.75, 0.83) *	0.96 (0.93, 1.00) +	0.90 (0.82, 0.98) +	0.84 (0.81, 0.87) *
	30–39 %	0.93 (0.88, 0.98) +	0.87 (0.82, 0.92) *	0.94 (0.90, 0.98) x	0.93 (0.85, 1.02)	0.91 (0.87, 0.94) *
	40 % and above	0.93 (0.87, 1.00)	0.79 (0.74, 0.84) *	0.98 (0.93, 1.02)	0.82 (0.73, 0.92) *	0.90 (0.86, 0.94) *
3	**Open grass % (ref = 0–9 %)**					
	10–19 %	0.99 (0.96, 1.03)	1.04 (1.01, 1.08) +	1.01 (0.99, 1.04)	0.99 (0.94, 1.05)	1.04 (1.02, 1.07) x
	20–29 %	1.03 (0.98, 1.07)	1.01 (0.97, 1.05)	1.01 (0.98, 1.04)	1.06 (0.99, 1.14)	1.05 (1.02, 1.08) x
	30 % and above	1.04 (0.96, 1.12)	1.06 (0.99, 1.14)	1.01 (0.96, 1.06)	1.11 (0.98, 1.26)	1.04 (0.98, 1.09)
Two green space variables model (trees + grass)						
4	**Tree canopy % (ref = 0–9 %)**					
	10–19 %	0.97 (0.92, 1.02)	0.87 (0.83, 0.91) *	1.00 (0.97, 1.03)	0.91 (0.84, 0.98) +	0.89 (0.86, 0.92) *
	20–29 %	0.94 (0.89, 0.99) +	0.79 (0.75, 0.83) *	0.96 (0.93, 1.00) +	0.91 (0.83, 0.99) +	0.85 (0.82, 0.88) *
	30–39 %	0.93 (0.87, 0.99) +	0.86 (0.81, 0.91) *	0.94 (0.90, 0.98) x	0.95 (0.86, 1.05)	0.91 (0.88, 0.95) *
	40 % and above	0.93 (0.86, 1.00)	0.78 (0.73, 0.84) *	0.98 (0.93, 1.02)	0.83 (0.74, 0.94) x	0.91 (0.86, 0.95) *
	Open grass % (ref = 0–9 %)					
	10–19 %	0.98 (0.95, 1.02)	1.01 (0.98, 1.04)	1.01 (0.99, 1.03)	0.98 (0.92, 1.04)	1.02 (1.00, 1.05)
	20–29 %	1.01 (0.97, 1.06)	0.96 (0.93, 1.01)	0.99 (0.96, 1.02)	1.04 (0.97, 1.12)	1.03 (1.00, 1.06)
	30 % and above	1.00 (0.93, 1.09)	0.97 (0.90, 1.04)	0.99 (0.94, 1.04)	1.07 (0.94, 1.22)	0.98 (0.93, 1.04)

GLM = generalised linear model || CI = confidence intervals || * $P \leq 0.001$, x $P \leq 0.01$, + $P \leq 0.05$; Model type 0. Incidence of any hospitalisation. (Mixing probability logistic model common to Models 1 to 3), built on the whole set; Model type 1. Total cost per year (GLM with gamma density); Model type 2. Mean cost of a hospitalisation per admission (GLM with gamma density); Model type 3a. Rate of hospitalisations per year (GLM with zero-truncated negative binomial density with offsets); Model type 3b. Rate of hospitalisations per year (GLM with gamma density); Model types 1 to 3b are conditional on the occurrence of admission; with respect to regression coefficients are built on a subset of participants with an admission; Modelling is done using SAS Proc FMM maximum likelihood algorithm || Second component of the models is constant zero density; Models are fitted with adjustment for all co-variates: gender, age, education, income, working and couple status.

CVD-related hospital admissions among individuals with more tree canopy nearby (Feng et al., 2023; Astell-Burt and Feng, 2020). Our analyses in this longitudinal cohort study with linked environmental and hospital admission data show that after adjusting for a range of confounders, the lower burden of cardiometabolic diseases and associated hospitalisations attributed to a 30 % tree canopy target translates into CVD event related health sector savings of AU$ 19.3 million per 100,000 people aged 45 years or older. Lower healthcare expenditures are likely to be a direct result of fewer hospitalisations occurring, for which rates of admission were consistently lower where tree canopy was greater than 10 % of land area, rather than due to lower means costs per admission which were not consistently associated with more tree canopy.

Our research extends research on green space and healthcare expenditure with one of the still very few cohort studies to track associations between different types of greenery and both incidence and cost of hospitalisations (Patwary et al., 2023). It complements findings from a recent study conducted in Northern California that reported similarly non-trivial health sector cost reductions among populations in the most versus least green areas (Van Den Eeden et al., 2022). It is notable that results from that study were driven by reduced hospital admissions and without restriction to CVD-related events. It is plausible due to the many ways in which contact with nature supports health that had we taken a similarly more expansive approach to disease burden and related healthcare utilisation, greater reductions in healthcare expenditure with more tree canopy may have been observed. However, our cautious and more restricted approach is justified by an intent to focus on a major health issue for which medical attention is essential and almost always sought after, and for which the putative pathways from green space are established (Markevych et al., 2017).

Our study is strengthened by the restricted focus on CVD-related hospitalisations. According to the National Heart Foundation of Australia, one person is hospitalised for a heart attack on average every 9 min (Johar et al., 2012). CVD remains a leading cause of morbidity and mortality for which links with nature contact are reasonably well established and medical attention is urgently sought. As our work on tree canopy has shown, more of it appears to help people to avoid or be more resilient to chronic stress (Astell-Burt and Feng, 2019; Feng et al., 2022), keep socially connected (Astell-Burt et al., 2023), maintain higher levels of physical activity (Feng et al., 2021) and healthier sleep hygiene (Astell-Burt and Feng, 2020), all of which contribute to lowering CVD risk. Layer upon this evidence that exposure to excess heat influences CVD risk (Mora et al., 2017) and that tree canopy can play a significant role in ameliorating the urban heat island effect (Jay et al., 2021). Likewise with the CVD-related harms of air pollution (Rajagopalan et al., 2018) and evidence that tree canopy can sometimes help to reduce exposure to it (Kumar et al., 2019). The cumulative impact of all these incremental benefits of tree canopy over time may be sustained heart health and lower risks of a heart attack or another major CVD-related event, thereby avoiding associated hospital costs.

This direct linkage between CVD events, healthcare use and expenditure is not always observed for other health conditions, for which it is common for only a fraction of individuals affected to receive the healthcare that could help them. Diabetes care, for instance, is undermined by a lack of detection (Meyerowitz-Katz et al., 2019; Hng et al., 2016). Another example is an increasing number of studies on green space which analyse anti-depressant medication prescribing or dispensing as a proxy for underlying depression (Astell-Burt et al., 2022; Helbich et al., 2018; McDougall et al., 2021; Taylor et al., 2015; Aerts et al., 2022; Marselle et al., 2020). This is problematic as prescription data does not affirm those medications were needed or used for depression (Chitty et al., 2019) – antidepressants can sometimes be used

Table 4
Predictions for the effects of planting trees to have 30 %+ in areas with 0 to 9 % of tree canopy.

Output	Tree canopy (%)	N	% of whole sample	Raw Means	Method 1 Means	Method 2 Means	Method 3 N	Method 3 Means
Total cost/year/person (full sample model)								
	0 to 9 %	13,545	12.30	765	814	729	13,545	814
	10 to 19 %	44,744	40.63	707	711	723	13,545	696
	20 to 29 %	26,914	24.44	636	648	698	13,545	622
	30 % and above	24,931	22.64	645	620	591	13,545	655
	Total sample	110,134	100	683	688	688	54,619	691
N episodes per year per person (full sample model)								
(full sample model)	0 to 9 %	13,545	12.30	0.0798	0.0829	0.0751	13,545	0.0829
	10 to 19 %	44,744	40.63	0.0739	0.0741	0.0759	13,545	0.0719
	20 to 29 %	26,914	24.44	0.0718	0.0719	0.0760	13,545	0.0673
	30 % and above	24,931	22.64	0.0721	0.0707	0.0672	13,545	0.0716
	Total sample	110,134	100	0.0737	0.0739	0.0739	54,691	0.0727
Mean cost per episode (subsample with costs model)								
	0 to 9 %	3,286	12.52	8701	8712	8679	3,286	8711
	10 to 19 %	10,756	40.99	8674	8672	8605	3,286	8677
	20 to 29 %	6,496	24.75	8306	8344	8430	3,286	8400
	30 % and above	5,705	21.74	8120	8085	8132	3,286	8285
	Total sample	26,243	100	8466	8468	8468	13,120	8534
	Calculations (Means, 95 % Confidence Intervals)							
Difference for tree canopy 30 % and above vs 0–9 %								
Total cost/year/person ($AU)				−119 (-259, 20)	−193 (-242, −145)	−138 (-183, −94)	−159 (-213, −104)	
Total cost/year/person ($AU) (sample with at least one episode)				−332 (-901, 237)	−569 (-736, −402)	−363(-517, −210)	−520 (-705, −335)	
N episodes per year per person				−0.008 (-0.020, 0.004)	−0.012 (-0.018, −0.006)	−0.008 (-0.014, −0.002)	−0.011 (-0.018, −0.005)	
Mean cost per episode				−581 (-1017, −145)	−627 (-915, −338)	−547 (-835, −259)	−426 (-751, −101	
Difference for 100,000 population shifted from less than 10 **% tree canopy to 30 %+**								
Total cost/year (million $AU)				−11.9 (-25.9, 20.0)	−19.3 (-24.2, −14.5)	−13.8 (-18.3, −9.4)	−15.9 (-21.3, −10.4)	
N episodes per year				−770 (-1950, 410)	−1220 (-1807, −633)	−790 (-1353, −227)	1130 (-1792, −468)	

Note, mean cost per episode has meaning only for the sample with episodes, same for predictions; Rate and n episodes per year make sense for the whole sample, same for predictions; All models are two-part gamma models with all covariates; Method 1 has tree canopy variable with 10% step as categories from 0 to 9% to 40% and above; Method 2 has tree canopy variable continuous; Method 3 has tree canopy variable with 10% step as categories from 0 to 9% to 30% and above; Predictions for Method 1 and 2 are aggregated over original trees categories, while predictions for Method 3 are calculated on the same sample of 0–9% trees area; $AU are Australian dollars; Variance for the means of predictions are calculated from sum of variance of each prediction from Proc FMM output, divided by n squared.

for 'off-label' purposes such as chronic pain and urinary incontinence. Records of antidepressant prescribing do not indicate whether non-recipients were supported by other proven remedies that were not measured and perhaps even preferred, such as talking therapies as a non-pharmacological alternative treatment (DeRubeis et al., 2008). Antidepressants may be discontinued because they can be ineffective (Crowe et al., 2023). Additionally, many people who need medical attention do not receive it, due to issues ranging from under-diagnosis to mental health stigma (Crowe et al., 2023). Unmet healthcare need varies geographically within and across national boundaries and is known to be especially severe in countries where universal health coverage is unavailable or healthcare is unaffordable to large numbers of people (e.g., the US, see Choi et al., 2020; Galvani et al., 2020).

In sum, health sector costs due to fewer healthcare interactions, dispensation of medications or referrals for psychological counselling and other specialist services for many other health issues that appear to be lower among populations with more green space may not always be directly attributable to green space provision, but to other systemic factors relating to how accessible, affordable, and accommodating healthcare is within a particular context. This may not necessarily be always for negative reasons, for instance, fewer antidepressant medications may be because doctors in some areas may be more likely to refer patients for talking therapies before taking a pharmaceutical option. As such, generalisation of healthcare expenditure in relation to green space and other upstream factors must consider the characteristics of local contexts, populations, and health systems. Our study may be more generalisable than most for its focus on healthcare expenditure due to CVD-related events within a country - Australia - that offers universal health coverage through Medicare. As noted in a recent review, the mechanisms linking green space and health may not necessarily be the same as the mechanisms linking green space and healthcare use and expenditure. We encourage future studies of green space and healthcare costs to lay out the hypothesised causal chain of events from exposure through biopsychosocial pathways to the health issue of concern, through the contrasting political, cultural, economic, and climatic contextual circumstances that then may influence whether those individuals who need healthcare receive it.

Another methodological note is the measurement of green space, which at once uses best-available high-resolution (2-m) land-use data to capture the entirety of vegetation available, with capacity to effectively differentiate between tree canopy and open grass; a consequential distinction based upon our findings and results of previous studies (e.g., Feng et al., 2023; Jiang et al., 2020). The data was only available from 2016 and so, with loss of vegetation over time, the quantity of green space measured should be considered a conservative estimate. A 1.6 km buffer was selected to reflect the lower density, car-centric and typically low-rise built environment common to cities in Australia. This size of buffer therefore accounts for potential population movements and cumulative opportunities for contact with green space beyond the smaller buffers sometimes analysed in denser contexts. This is a contextually-dependent selection with research from Australia showing, for example, that the social health benefits of green space are hidden when considering buffers of 400 m to 800 m, but observable for 1.6 km buffers (Astell-Burt et al., 2022). This does not dismiss the importance of other factors that influence contact with green space not captured by the data to which we had access and provide avenues for further research, such as levels of amenity, accessibility, aesthetics, felt safety and other qualities that make some green spaces worth visiting and render others as places to avoid (Nguyen et al., 2021; Astell-Burt and Feng, 2022). Similarly, other contextual factors might contribute to the outcomes examined in our study, such as variations in hospital quality and the distance or travel-time between where a person was at the time they experienced a heart attack and the hospital to which they were taken. Data on the exact hospital to which a person was taken and its precise location was unavailable so these could not be examined. Further studies might aim to examine how these issues might vary the associations reported in our work, as well as other potential sources of contingency such as other contextual characteristics such as intersections between green space and urban sprawl (Richardson et al., 2012), walkability (Roscoe et al., 2022) or housing type (Feng et al., 2022; Feng et al., 2021). Indeed, this may also help to explain the largely null or counterintuitive associations between healthcare expenditure and open grass in our study. As we have previously discussed, it seems likely that poorer health among some individuals in areas with large amounts of open grass may be related to derelict and low quality greenery that many will not find attractive or safe to visit for social purposes or physical recreation, while also potentially increasing the distances of travel to levels that discourage walking and foster car dependency, all of which have health penalties over time (Astell-Burt and Feng, 2019).

The bottom line from our study is that when examining the number one cause of death worldwide – CVD – our findings robustly show expectations that investing in tree canopy cover in cities helps to reduce healthcare expenditure by keeping people healthy and out of hospital. This evidence can provide additional impetus to existing and new greening strategies and the planners and health professionals who champion them, for their improvements in community and planetary health.

5. Data sharing

Data is available strictly under licence from The Sax Institute (https://www.saxinstitute.org.au) via the Secure Unified Research Environment (SURE).

CRediT authorship contribution statement

Xiaoqi Feng: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Michael Navakatikyan:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Simon Eckermann:** Conceptualization, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing. **Thomas Astell-Burt:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2024.108558.

References

[1] NWAU Calculators, 2013–14. 2014.. https://www.ihpa.gov.au/sites/default/files/publications/excel_macro-enabled_workbook-nwau13_calculator_for_acute_admitted_activity_excel_97-2003.xls.
[2] Heart Attack., 2024 https://www.heartfoundation.org.au/bundles/your-heart/heart-attack.
45 and Up Study Collaborators. Cohort Profile: The 45 and Up Study. Int Journal of Epidemiology 2008; **37**(5): 941-7.
Aerts, R., Vanlessen, N., Dujardin, S., et al., 2022. Residential green space and mental health-related prescription medication sales: an ecological study in Belgium. Environ. Res. 211, 113056.
Astell-Burt, T., Feng, X., 2019. Association of Urban Green Space with Mental Health and General Health among Adults in Australia. JAMA Netw. Open 2 (7), e198209.
Astell-Burt, T., Feng, X., 2020. Urban green space, tree canopy and prevention of cardiometabolic diseases: a multilevel longitudinal study of 46 786 australians. Int. J. Epidemiol. dyz239.
Astell-Burt, T., Feng, X., 2020. Does sleep grow on trees? a longitudinal study to investigate potential prevention of insufficient sleep with different types of urban green space. SSM-population. Health, 100497.
Astell-Burt, T., Feng, X., 2022. Paths through the woods. Oxford University Press, pp. 1–5.
Astell-Burt, T., Hartig, T., Eckermann, S., et al., 2022. More green, less lonely? a longitudinal cohort study. Int. J. Epidemiol. 51 (1), 99–110.
Astell-Burt, T., Hartig, T., Putra, I.G.N.E., Walsan, R., Dendup, T., Feng, X., 2022. Green space and loneliness: a systematic review with theoretical and methodological guidance for future research. Sci. Total Environ., 157521
Astell-Burt, T., Navakatikyan, M., Eckermann, S., Hackett, M., Feng, X., 2022. Is urban green space associated with lower mental healthcare expenditure? Soc Sci Med 292, 114503.
Astell-Burt, T., Walsan, R., Davis, W., Feng, X., 2023. What types of green space disrupt a lonelygenic environment? a cohort study. Soc. Psychiatry Psychiatr. Epidemiol. 58 (5), 745–755.
Bleicher, K., Summerhayes, R., Baynes, S., et al., 2023. Cohort profile update: the 45 and up study. Int. J. Epidemiol. 52 (1), e92–e101.
Chen, H., Burnett, R.T., Bai, L., et al., 2020. Residential greenness and cardiovascular disease incidence, readmission, and mortality. Environ. Health Perspect. 128 (8), 087005.
Chitty, K., Butterworth, P., Batterham, P., 2019. Antidepressant use and its relationship with current symptoms in a population-based sample of older australians. J. Affect. Disord. 258, 83–88.
Choi, N.G., DiNitto, D.M., Choi, B.Y., 2020. Unmet healthcare needs and healthcare access gaps among uninsured US adults aged 50–64. Int. J. Environ. Res. Public Health 17 (8), 2711.
Crowe, M., Inder, M., McCall, C., 2023. Experience of antidepressant use and discontinuation: a qualitative synthesis of the evidence. J. Psychiatr. Ment. Health Nurs. 30 (1), 21–34.
Dalton, A., Jones, A., 2020. Residential neighbourhood greenspace is associated with reduced risk of cardiovascular disease: a prospective cohort study. PLoS One 15 (1), e0226524.
DeRubeis, R.J., Siegle, G.J., Hollon, S.D., 2008. Cognitive therapy versus medication for depression: treatment outcomes and neural mechanisms. Nat. Rev. Neurosci. 9 (10), 788–796.
Feng, X., Astell-Burt, T., 2022. Lonelygenic environments: a call for research on multilevel determinants of loneliness. The Lancet Planetary Health 6 (12), e933–e934.
Feng, X., Toms, R., Astell-Burt, T., 2021. Association between green space, outdoor leisure time and physical activity. Urban For. Urban Green. 66, 127349.
Feng, X., Toms, R., Astell-Burt, T., 2022. The nexus between urban green space, housing type, and mental health. Soc. Psychiatry Psychiatr. Epidemiol. 57 (9), 1917–1923.

Feng, X., Navakatikyan, M.A., Toms, R., Astell-Burt, T., 2023. Leafier communities, healthier hearts: an australian cohort study of 104,725 adults tracking cardiovascular events and mortality across 10 years of linked health data. Heart Lung Circ. 32 (1), 105–113.
Frumkin, H., 2003. Healthy places: exploring the evidence. Am. J. Public Health 93 (9), 1451.
Fu, X., Xu, J., Zhang, R., Yu, J., 2020. The association between environmental endocrine disruptors and cardiovascular diseases: a systematic review and meta-analysis. Environ. Res. 187, 109464.
Galvani, A.P., Parpia, A.S., Foster, E.M., Singer, B.H., Fitzpatrick, M.C., 2020. Improving the prognosis of health care in the USA. Lancet 395 (10223), 524–533.
Gidlow, C.J., Smith, G., Martinez, D., et al., 2016. Research note: natural environments and prescribing in England. Landsc. Urban Plan. 151, 103–108.
Helbich, M., Klein, N., Roberts, H., Hagedoorn, P., Groenewegen, P.P., 2018. More green space is related to less antidepressant prescription rates in the Netherlands: a bayesian geoadditive quantile regression approach. Environ. Res. 166, 290–297.
Hng, T.-M., Hor, A., Ravi, S., et al., 2016. Diabetes case finding in the emergency department, using HbA1c: an opportunity to improve diabetes detection, prevention, and care. BMJ Open Diabetes Res. Care 4 (1), e000191.
Independent Hospital Pricing Authority (IHPA). Explanatory Notes for the 2012-13 Excel NWAU Calculators. March 2013. 2013. https://www.ihpa.gov.au/sites/default/files/publications/nwau13-calculator-user-guide.pdf.
Independent Hospital Pricing Authority (IHPA). National Pricing Model Technical Specification 2012-2013. Version 1.1. . 2013. https://www.ihpa.gov.au/sites/default/files/publications/nationalpricingmodeltechnicalspecification2012-13.pdf.
Jacobsen, A.P., Khiew, Y.C., Duffy, E., et al., 2022. Climate change and the prevention of cardiovascular disease. *american journal of*. Prev. Cardiol., 100391
Jay, O., Capon, A., Berry, P., et al., 2021. Reducing the health effects of hot weather and heat extremes: from personal cooling strategies to green cities. Lancet 398 (10301), 709–724.
Jiang, X., Larsen, L., Sullivan, W., 2020. Connections between daily greenness exposure and health outcomes. Int. J. Environ. Res. Public Health 17 (11), 3965.
Johar, M., Jones, G., Savage, E., 2012. Healthcare expenditure profile of older australians: evidence from linked survey and health administrative data. Economic Papers: A Journal of Applied Economics and Policy 31 (4), 451–463.
Kessler D, McDowell A. Introducing the FMM Procedure for Finite Mixture Models SAS Paper 328-2012 (page 22). 2012. https://support.sas.com/resources/papers/proceedings12/328-2012.pdf.
Khraishah, H., Alahmad, B., Ostergard Jr, R.L., et al., 2022. Climate change and cardiovascular disease: implications for global health. Nat. Rev. Cardiol. 19 (12), 798–812.
Kondo, M.C., Mueller, N., Locke, D.H., et al., 2020. Health impact assessment of Philadelphia's 2025 tree canopy cover goals. The Lancet Planetary Health 4 (4), e149–e157.
Kumar, P., Druckman, A., Gallagher, J., et al., 2019. The nexus between air pollution, green infrastructure and human health. Environ. Int. 133, 105181.
Liu, X.-X., Ma, X.-L., Huang, W.-Z., et al., 2022. Green space and cardiovascular disease: a systematic review with meta-analysis. Environ. Pollut. 301, 118990.
Lopez, A.D., Adair, T., 2019. Is the long-term decline in cardiovascular-disease mortality in high-income countries over? evidence from national vital statistics. Int. J. Epidemiol. 48 (6), 1815–1823.
Marashi, A., Ghassem Pour, S., Li, V., Rissel, C., Girosi, F., 2019. The association between physical activity and hospital payments for acute admissions in the australian population aged 45 and over. PLoS One 14 (6), e0218394.
Markevych, I., Schoierer, J., Hartig, T., et al., 2017. Exploring pathways linking greenspace to health: theoretical and methodological guidance. Environ. Res. 158, 301–317.
Marselle, M.R., Bowler, D.E., Watzema, J., Eichenberg, D., Kirsten, T., Bonn, A., 2020. Urban street tree biodiversity and antidepressant prescriptions. Sci. Rep. 10 (1), 22445.
McDougall, C.W., Hanley, N., Quilliam, R.S., et al., 2021. Neighbourhood blue space and mental health: a nationwide ecological study of antidepressant medication prescribed to older adults. Landsc. Urban Plan. 214, 104132.
Meyerowitz-Katz G, Seelan S, Gaur P, et al. Detecting the hidden burden of pre-diabetes and diabetes in Western Sydney. *diabetes research and clinical practice* 2019; **151**: 247-51.
Mora, C., Counsell, C.W., Bielecki, C.R., Louis, L.V., 2017. Twenty-seven ways a heat wave can kill you: deadly heat in the era of climate change. Circ. Cardiovasc. Qual. Outcomes 10 (11), e004233.
Münzel, T., Sørensen, M., Lelieveld, J., et al., 2021. Heart healthy cities: genetics loads the gun but the environment pulls the trigger. Eur. Heart J. 42 (25), 2422–2438.
Nguyen, P.-Y., Astell-Burt, T., Rahimi-Ardabili, H., Feng, X., 2021. Green space quality and health: a systematic review. Int. J. Environ. Res. Public Health 18 (21), 11028.
Patwary, M.M., Bardhan, M., Browning, M.H., et al., 2023. The economics of nature's healing touch: a systematic review and conceptual framework of green space, pharmaceutical prescriptions, and healthcare expenditure associations. Sci. Total Environ. 169635.
Rajagopalan, S., Al-Kindi, S.G., Brook, R.D., 2018. Air pollution and cardiovascular disease: JACC state-of-the-art review. J. Am. Coll. Cardiol. 72 (17), 2054–2070.
Richardson, E.A., Mitchell, R., Hartig, T., De Vries, S., Astell-Burt, T., Frumkin, H., 2012. Green cities and health: a question of scale? J Epidemiol Community Health 66 (2), 160–165.
Roscoe, C., Sheridan, C., Geneshka, M., et al., 2022. Green walkability and physical activity in UK biobank: a cross-sectional analysis of adults in greater London. Int. J. Environ. Res. Public Health 19 (7), 4247.
Roth, G.A., Johnson, C., Abajobir, A., et al., 2017. Global, regional, and national burden of cardiovascular diseases for 10 causes, 1990 to 2015. J. Am. Coll. Cardiol. 70 (1), 1–25.
SAS Institute Inc. SAS/STAT® 14.1 User's Guide. Chapter 39 The FMM Procedure (pages 2478-2597). 2015. https://support.sas.com/documentation/onlinedoc/stat/141/fmm.pdf2023).
Seo, S., Choi, S., Kim, K., Kim, S.M., Park, S.M., 2019. Association between urban green space and the risk of cardiovascular disease: a longitudinal study in seven korean metropolitan areas. Environ. Int. 125, 51–57.
Taylor, M.S., Wheeler, B.W., White, M.P., Economou, T., Osborne, N.J., 2015. Research note: urban street tree density and antidepressant prescription rates—A cross-sectional study in London. UK. *Landscape and Urban Planning* 136, 174–179.
Van Den Eeden, S.K., Browning, M.H., Becker, D.A., et al., 2022. Association between residential green cover and direct healthcare costs in northern California: an individual level analysis of 5 million persons. Environ. Int. 163, 107174.
Wolf, K.L., Measells, M.K., Grado, S.C., Robbins, A.S., 2015. Economic values of metro nature health benefits: a life course approach. Urban For. Urban Green. 14 (3), 694–701.
Yu, Y., Davey, R., Cochrane, T., Learnihan, V., Hanigan, I.C., Bagheri, N., 2017. Neighborhood walkability and hospital treatment costs: a first assessment. Prev. Med. 99, 134–139.