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Is urban green space associated with lower mental healthcare expenditure?

--Manuscript Draft--

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Abstract:	Introduction While the evidence of mental health benefits from investing in green space accumulates, claims of reduced healthcare expenditure are rarely supported by evidence from analyses of actual healthcare data. Additionally, the question of 'who pays?' has been ignored. We addressed these gaps using person-level data in three Australian cities. Methods 55,339 participants with a mean follow-up time of 4.97 years in the Sax Institute's 45 and Up Study (wave 2, collected 2012-2015) were linked to fee-for-service records of antidepressant prescriptions and talking therapy subsidised by the Australian Government (including data on per unit fee, state subsidy, and individual co-payment). Total green space, tree canopy and open grass within 1.6km road network distances were linked to each participant. Multilevel logistic, zero-truncated negative binomial, and generalised linear models with gamma distribution adjusted for demographic and socioeconomic confounders were used to assess association between each green space variable and prescribing/referral and costs of antidepressants and talking therapy. Results Prescription of at least one course of antidepressants occurred for 20.01% (n=11,071). Referral for at least one session of talking therapy occurred in 8.95% (n=4,954). 13,482 participants (24.4%) either prescription or referral. A 10% increase in green space was associated with higher levels of antidepressant prescribing (e.g. incident rate ratio (IRR)=1.05, 95%CI=1.04-1.08). Tree canopy was not associated with antidepressant prescribing or referrals for talking therapy. Open grass was associated with higher odds (OR=1.17, 95%CI=1.13-1.20) and counts (IRR =1.06, 95%CI=1.03-1.08) of antidepressant prescriptions. Open grass was also associated with lower odds (OR=0.87, 95%CI=0.82-0.92) and counts (IRR=0.93, 95%CI=0.90-0.96) of talking therapy referrals. Open grass was associated with higher total and mean per-person levels of expenditure on antidepressant prescriptions. Conclusion Although green space supports mental health, these unexpected results provide pause for reflection on whether greening strategies will always result in purported reductions in mental healthcare expenditure.

Reviewer #1: Thank you for giving me the opportunity to review the revised version of the paper. I appreciate the authors' responses to my, and other reviewers' comments, but I still have serious reservations about the paper. In addition, some of my original comments below (number 7) were not addressed at all.

Authors response: Thank you for providing further comments on our manuscript.

Reviewer #1.1: As I mentioned before, one of the most difficult issues to deal with in these types of studies is selection, i.e., the fact that those with better socioeconomic status and health are more likely to live in areas with better environmental conditions. While the authors have now included a clearer description of how the models are adjusted for confounding by observable characteristics, Supplementary Table 6 was not provided to me in the revised documents I received. The authors mention 'unmeasured wealth' but this is not the only unmeasured factor I am concerned about - unmeasured health (particularly mental health) status may also bias the observed associations.

Authors response: We have re-submitted the Supplementary Table file and hope that it is received this time. Unmeasured wealth is identified as an example of a potential source of confounding. Unmeasured health, and mental health in particular, is not a confounder as it is hypothesised to lie on the causal pathway between green space availability and mental healthcare use i.e. green space improves mental health, which in turn, reduces demand for mental healthcare. Adjustment for mental health in these models would induce instead of reduce bias, so this was not done.

Reviewer #1.2: Again, Supplementary Figure 1 (the new data flow chart) was not provided to me. However, the description in the text still does not make sense to me:
'Supplementary figure 1 reports the derivation of the analytical sample of 55,399. In brief, a total of 55,388 participants were retained from the 141,014 follow-up sample as they were residing in one of Sydney, Newcastle or Wollongong (omitting 85,626 living in other areas of NSW). A further 49 participants were omitted as they had opted to withdraw their participation in the 45 and Up Study, reducing the sample from 55,388 to the final analytical sample of 55,399'.
How can the last sentence be correct? There is a difference of only 11 observations between 55,388 and 55,399, and the final analytical sample (55,399) is larger than the former figure (55,388)?

Authors response: We have re-submitted the Supplementary Table file and hope that it is received this time. The stated final analytical sample of 55,399 had a typo and should have said 55,339 (55,388 – 49). The text has been corrected accordingly and aligns with figures in the flowchart.

Reviewer #1.3: Thank you for providing more detail on the Australian Medicare system. However, from my reading of the new text, it seems as if those who are not concession cardholders pay more out of pocket for prescription medications, regardless of whether the medication is above or below the $41.30 threshold. If the cost of the medication is below $41.30, non-concession cardholders (presumably those on higher incomes) pay the full cost, while for medications above $41.30, they pay $41.30 (and concession cardholders only pay $6.60). The results in Figure 3 may also therefore by explained by the fact that those living in areas with more green space (who are more socioeconomically advantaged) simply pay more out-of-pocket for medications.

Authors response: We are in broad agreement with this description. We add this reflection into our Discussion section. However, in this case the higher costs are with people who live in areas with more open grass, which tends to be people on lower incomes or least educational attainment, as shown in Supplementary Table 6 (we realise that supplementary materials were not previously made previously available). The Discussion section has been revised accordingly.

Reviewer #1.4: My original point 7, replicated here, was not addressed in the revision. 'For all models however, I was confused by the choice of estimation method and the way in which the results were presented. For the results in Supplementary Tables S3 and S4, it seems that multilevel techniques were used, presumably with 'mesh area' as the first level? For the models in Supplementary Table S5, there is no mention of multilevel modelling. In addition, given the way in which the green space variables are constructed (categories of cover), how can the authors present results for a 10% increase in green space? Surely that could only be possible if the green space variables were entered as continuous variables? On that latter point, why did the authors not just use continuous values for the green space, tree canopy and open grass variables?'

Authors response: All models were fitted with random effects on geographic areas (Statistical Area 3). This is already specified in the Methods-Statistical Analysis section. We have added some more wording to make this clearer in the Methods section, as well as the titles of the relevant tables and figures. All green space variables were formatted in so that a 1-unit difference was equivalent to a 10% difference in green space availability (i.e. by dividing each green space variable by 10). This reformatting provides a more valuable estimate for end-users without leading to any loss in accuracy. We have edited the text to ensure that this is also clearer.

Reviewer #1.5: Again, my original point 8 (replicated below) was not fully addressed. Why are hazard models not appropriate? Some adjustment needs to be made for the varying length of follow-up (which may not necessarily be always due to death but could presumably be due to reasons such as emigration?). However, my main methodological issue relates to the way in which the time dimension of the data is taken into account. The authors mention that the mean follow-up period was 4.97 years. Were the outcome variables adjusted to take into account the varying length of follow-up for each individual in the sample? Why were alternative methods such as hazard models not considered? I feel that this is one of the key problems with the analyses in the paper, and may partly account for the counterintuitive results - if those who live in areas with more green space had a shorter follow-up period, then this might account for the finding that their use of, and expenditure on, antidepressants was lower than those living in areas with less green space.

Authors response: We have recalculated all of the models, using either adjustment for length of follow-up as a covariate or exposure time as an offset, depending upon the model. This approach was taken as previous work indicates cox proportional hazards models because attrition due to death was very low (just 2.7%) and it was evenly distributed across green space variables. Furthermore, cox proportional hazards models are challenging to interpret when used to model healthcare costs (Austin et al, 2003; Diehr et al, 1999). Taking the approach outlined above is more intuitive but has nonetheless taken substantial time to implement, as all models have been re-run. The updated results are mostly consistent despite this adjustment, which is expected as the maximum follow-up time was 5 years and the mean follow-up time was 4.97 years. Every table and figure presenting modelled results has subsequently been updated. The Methods and Results text has also been updated.

Austin PC, Chali WA, Tu JV. A comparison of several regression models for analysing cost of CABG surgery. *Statist. Med.* 2003; **22**:2799–2815.

Diehr P, Yanez D, Ash A, Hornbrook M, Lin DY. Methods for analyzing health care utilization and costs. *Annu. Rev. Public Health*. 1999. **20:**125–44

Reviewer #1.6: Finally, the authors add some new references (23-25) that use the same data, but in the case of 23, find very different results to those reported in the current study. How can these results be reconciled?

Authors response: Findings from reference 23 indicate reduced odds of psychological distress among people with more tree canopy nearby, but also higher odds of psychological distress among those with more open grass nearby. This was also reported by a different set of investigators using data from the US (reference 39). In the previous revision we confirmed that these associations were replicated in the current sample (see the subheading 'Further Analyses' within the 'Results' section). Our updated analyses indicate that higher odds and counts of antidepressants are associated with more open grass, which is associated with higher odds of psychological distress, so this makes sense. We also find higher mental healthcare costs are associated with open grass, which also makes sense, though seems to be also partially explained by higher mean healthcare costs among people with more open grass nearby. We have amended the Discussion section with these details.

Reviewer #3: The authors have comprehensively addressed the reviewer's concerns raised with the limitations of the study design and data.

Authors response: Thank you for confirming our response was satisfactory.

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Dear Professor Coast,

Thank you for considering our revised manuscript for publication in Social Science & Medicine (SSM).

We note that Reviewer 1 has made several points and reiterated some they felt had previously not been attended to sufficiently. Accordingly, we have re-analysed all of our data to ensure that this time, their recommendations are fully attended to.

Edits to the manuscript are in blue font. We have responded to all of the reviewers second round of comments.

Kind regards
Thomas Astell-Burt

ABSTRACT

Introduction

While the evidence of mental health benefits from investing in green space accumulates, claims of reduced healthcare expenditure are rarely supported by evidence from analyses of actual healthcare data. Additionally, the question of 'who pays?' has been ignored. We addressed these gaps using person-level data in three Australian cities.

Methods

55,339 participants with a mean follow-up time of 4.97 years in the Sax Institute's 45 and Up Study (wave 2, collected 2012-2015) were linked to fee-for-service records of antidepressant prescriptions and talking therapy subsidised by the Australian Government (including data on per unit fee, state subsidy, and individual co-payment). Total green space, tree canopy and open grass within 1.6km road network distances were linked to each participant. Multilevel logistic, zero-truncated negative binomial, and generalised linear models with gamma distribution adjusted for demographic and socioeconomic confounders were used to assess association between each green space variable and prescribing/referral and costs of antidepressants and talking therapy.

Results

Prescription of at least one course of antidepressants occurred for 20.01% (n=11,071). Referral for at least one session of talking therapy occurred in 8.95% (n=4,954). 13,482 participants (24.4%) either prescription or referral. A 10% increase in green space was associated with higher levels of antidepressant prescribing (e.g. incident rate ratio (IRR)=1.05, 95%CI=1.04-1.08). Tree canopy was not associated with antidepressant prescribing or referrals for talking therapy. Open grass was associated with higher odds (OR=1.17, 95%CI=1.13-1.20) and counts (IRR =1.06, 95%CI=1.03-1.08) of antidepressant prescriptions. Open grass was also associated with lower odds (OR=0.87, 95%CI=0.82-0.92) and counts (IRR=0.93, 95%CI=0.90-0.96) of talking therapy referrals. Open grass was associated with higher total and mean per-person levels of expenditure on antidepressant prescriptions.

Conclusion

Although green space supports mental health, these unexpected results provide pause for reflection on whether greening strategies will always result in purported reductions in mental healthcare expenditure.

Keywords

Green space, tree canopy, antidepressant, talking therapy, mental health, healthcare cost

Open grass was associated with antidepressants prescribing

Open grass was associated with higher mental healthcare costs

Tree canopy was not associated with mental healthcare expenditure

Is urban green space associated with lower mental healthcare expenditure?

INTRODUCTION

Over 70% of the world's population is expected to live in cities by the year 2050.[1] The shift in planning away from sprawling low density metropolises to increasingly compact cities through processes of urban regeneration and in-fill housing has strong public health support.[2 3] But this shift also provokes unease among some conservationists, urban planners, landscape architects and others concerned with losses in biodiversity and urban green space.[4 5] Globally, people advocate for investment in urban green space and tree canopy [6] by claiming it will help to avert the climate crisis, mitigate water shortages, prevent a sixth mass extinction, improve liveability and strengthen community health.[7-9] A key component of this advocacy is a purported reduction in healthcare expenditure. For example, Public Health England's "Improving access to green space: A new review for 2020" report[10] claimed *"£2.1 billion per year could be saved in health fees if everyone in England had good access to greenspace…"* (pp.12).

Meta-analyses of experimental and epidemiological studies indicate evidence for urban green spaces providing opportunities for stress relief[11] and renewal of depleted cognitive capacities for optimal executive functioning.[12 13] This *'restoration'* pathway is based on established theories of stress reduction[14 15] and attention restoration.[16 17] Restoration and stress reduction are highly related to human behaviour that helps to build health capacities, such as social interaction and physical activity. A third pathway is the extent to which urban greening may provide community-wide reductions in ambient hazards, such as temperature cooling,[18] air quality filtering[19] and buffering of excess noise.[20] Together, these pathways may lower the risk of non-communicable diseases[21] and premature death.[22] Accordingly, one might hypothesise that the health benefits accrued by populations resident in areas with more green space will translate into reduced healthcare use and lower levels of health expenditure.

While the evidence for investing in green space for health benefit increases (e.g. our work in Australian cities indicate restoring urban tree canopy to $\geq$30% of local land-use are associated with reduced levels of incident psychological distress,[23] cardiometabolic diseases,[24] and dementia[25]), it is rare for claims of reduced healthcare expenditure to be based upon analysis of actual healthcare use. In most studies estimates are based on projections,[26] quality-adjusted life years[27 28] or 'value of statistical life'.[29] Analysis of actual healthcare data is critically important to understand the true relative costs involved and who is bearing them. We know that many people who need healthcare do not receive it[30] so investment in green space as an adjunct to formal healthcare is an appealing hypothesis.[31] Conversely however, increased longevity may result in *increased* healthcare use and fees.[32] In many countries a patient co-payment is required for certain types of healthcare (e.g. medications). The question of 'who pays?' adds an equity dimension that has been previously ignored.

Some researchers have focussed on prescribing patterns in healthcare without analysing costs when determining the impact of green space. Reductions in dispensing of antidepressant medication was found within municipalities in the Netherlands where total green space reached 28% land-cover or greater,[33] and in boroughs in London (UK) with higher street tree density.[34] Lower odds of antidepressant prescribing were observed with more street trees but only among people in less favourable socioeconomic circumstances in a German study.[35] In Spain, a study reported lower odds of self-reported antidepressants by people in greener neighbourhoods.[36] In contrast, a study spanning the whole of England reported no difference in antidepressant prescribing in neighbourhoods with more green space, but there were *higher* rates of prescribing and spending on cardiovascular medications.[37] Mixed results have also been found in the US, with less Medicare spending seen in counties with more forest and shrub, but not in counties with more agricultural land, urban vegetation or grass cover.[38]

Several questions remain unanswered. Do the reductions in antidepressant prescribing indicate less need for antidepressants due to better population mental health, or perhaps an inability of individuals to afford the consultation fee and/or costs of antidepressants prescribed in contexts where medications are not covered by universal healthcare? While both scenarios assume cost-savings, one is indicative of benefit and the other of potential harm. Furthermore, does the type of green space matter? This is pertinent to ask given several of the aforementioned studies reported lower antidepressant prescribing and/or lower Medicare costs in areas specifically with more tree canopy,[34 35 38] but the US study not finding comparable results for areas with more open grass. Previous work has reported contrasting associations between these types of green space and indicators of mental health. More favourable mental health has been reported among populations with more tree canopy nearby, but with null or worse outcomes with more open grass,[23 39 40] indicating the potential for flow-on impacts and contrasting associations with mental healthcare use and costs.

Limited and conflicting cost analyses indicate a need for research specifically designed to determine whether urban greening strategies can lead to reduced healthcare expenditure. An important current limitation of all previous studies using healthcare claims data to assess association with green space is that they have been ecological and susceptible to ecological fallacy (the mistaken assumption that associations observed at a group or population level always apply at the individual level[41]) and to biases related to scale and the modifiable areal unit problem (different ways of delineating area boundaries can manipulate data aggregation to confound direction and magnitude of associations).[42 43] A lack of adjustment for individual-level socioeconomic circumstances in ecological studies may leave studies vulnerable to residual confounding given various studies reporting more affluent groups tending to have access to more green space.[25 44 45] Further, this lack of adjustment may have other implications for model validity of samples within countries where healthcare access is strongly dependent upon income, educational attainment and employment, especially where universal healthcare coverage is absent or does not cover all healthcare costs.

We analysed associations between different types of green space and per-person expenditure on mental healthcare recorded in a large sample of individuals resident in three Australian cities. Use of individual-level data permitted adjustment for a range of potential socioeconomic confounders including income, education and employment status, eliminating the limitations of previous ecological studies. Given reported loss of contact with green space in urban areas and links between green space and mental health within rural areas being potentially bound up with contextual issues such as agricultural pesticide use[46] and drought,[47] our focus was on residents in the cities of Sydney, Newcastle and Wollongong, the three largest cities in the Australian state of New South Wales (NSW). We further contrasted patterns of association with two types of mental healthcare (prescribing of antidepressant medications and referral for talking therapy) along with their relative costs to society and, where applicable, co-payments made by individuals, to quantify potential impacts on equity.

METHODS

Data

Participants in the Sax Institute's 45 and Up Study[48] were recruited between 2006 and 2009 from residents of NSW. People aged 45 years or older listed in the Services Australia (formerly the Department of Human Services) enrolment database (Australia's universal healthcare system, available to Australian and New Zealand citizens residing in Australia, as well as permanent residents in Australia and people from other selected countries[49]). Interested participants completed a questionnaire, resulting in an 18% response rate and a baseline sample of 267,153 people with a demographic profile that was broadly representative of the population aged $\geq$45 years in Australia.[50] Participants in our study were selected from the second full follow-up wave (N=141,014) recruited between 2012 and 2015.

Supplementary figure 1 reports the derivation of the analytical sample of 55,339. In brief, a total of 55,388 participants were retained from the 141,014 follow-up sample as they were residing in one of Sydney, Newcastle or Wollongong (omitting 85,626 living in other areas of NSW). A further 49 participants were omitted as they had opted to withdraw their participation in the 45 and Up Study, reducing the sample from 55,388 to the final analytical sample of 55,339. Participants were censored at December 31st 2016 or earlier in the case of death. Records of death were ascertained via probabilistic linkage to the NSW Register for Births, Marriages and Deaths performed by the Centre for Health Record Linkage (https://www.cherel.org.au/). The average time observed for each participant between completion of the follow-up survey and either death or censoring was 4.97 years (0.8 min, 5.0 max).

The 45 and Up Study received ethics approval from the UNSW Human Research Ethics Committee (HREC). This study was approved by the University of Wollongong HREC and the NSW Population and Health Services Research Committee. Participants in the 45 and Up Study provided written informed consent for their responses to be linked to other data sources for the purposes of research.

Linkage to green space variables

The centroid of the 'Mesh Block' in which each participant resided was used as a proxy for their home address. Mesh Blocks are created by the Australian Bureau of Statistics (ABS) and are very small in both geographic area and in population, containing between 30 and 60 dwellings. Larger Mesh Blocks denoting inland water bodies, parklands, hospitals, industrial zones and educational precincts can be substantially larger, but these were not used as proxies for home addresses as they are not typically occupied. A 1.6km road network distance was used to create catchment areas for each participant, within which the percentage of land-use covered in green space was calculated. The 1.6 km distance was selected based upon published guidance around travel distances by foot[51] to capture cumulative opportunities for contact with green space near the home.[52] Green space was measured using 2-m raster surface land-use data acquired from Pitney Bowes Ltd for 2016 ('Geovision'). These data permitted calculation of three green space variables inclusive of private (e.g. gardens, back yards) or public (e.g. parks and reserves) land-use:

1. Percentage total green space, including tree canopy, open grass, and shrub
2. Percentage tree canopy, including deciduous and evergreen trees;
3. Percentage open grass that was not under tree canopy.

For descriptive purposes, each of these green space variables were stratified into categories aligned with peaks in distributions (close to arithmetic or geometric intervals), and planning standards for green space already in use (e.g. 10% of subdivisible land is allocated to green space in Perth, Western Australia[53]). The categories were: (i) total green space = 0-24.9%, 25.0-31.9%, 32.0-39.9%, 40.0-49.9%, $\geq$50.0%; (ii) tree canopy = 0-9.9%, 10.0-19.9%, 20.0-29.9%, $\geq$30.0%; (iii) open grass = 0-4.9%, 5.0-9.9%, 10.0-19.9%, $\geq$20.0%. Statistical analyses involved estimating associations for a putative 10% increase in each green space variable, using original continuous variable divided by 10. Shrub was not analysed as a separate type of green space because (i) it constitutes a minority land-use that may not be open to human interaction, (ii) urban greening policies tend to focus on tree planting and/or conservation of grassy areas conducive to sports and recreation, and (iii) open grass and tree canopy variables were fitted into models simultaneously, shrub omission avoids multicollinearity.

Outcome variable selection and implications for the analytical sample

Deterministic methods were used by the Sax Institute to link participant responses to records of mental healthcare prescription and fees listed on the Medicare Benefits Schedule (MBS) and Pharmaceutical Benefits Scheme (PBS) up to December 31st 2016 received from Services Australia. The MBS and PBS comprise lists of medical services and prescription medicines for which a rebate (i.e. 'benefit') is paid by the Australian Government to provide financial assistance towards the overall medical fee. It warrants noting that all Medicare Card holders irrespective of socioeconomic circumstances receive the full subsidy on prescriptions listed on the PBS and on referrals listed on the MBS. However, there can still be a charge for the patient depending upon the healthcare received. For example, on the MBS, the state covers 100% of the fee for consulting a GP. But the state covered 85% (AUD $129.55; 2021 costs) of the AUD $152.40 referral fee by a GP to a registered clinical psychologist for a minimum of 50 minutes for psychological assessment and therapy for a mental disorder (MBS item number 80010). In this case, the remaining 15% of the fee would form a co-payment paid by the patient (hereafter referred to as a 'contribution').

The PBS subsidises medications costing more than AUD $41.30 per prescription, with general patients will paying no more than this amount and concessionaries (pensioners, health care card holders, Commonwealth seniors health card holders and veterans card holders) paying no more than AUD $6.60. In cases where the dispensed cost of a medication is below AUD $41.30, the subsidy does not apply and non-concessionary patients are required to contribute the full cost (i.e. 'under co-payment'). For example, sertraline hydrochloride is among the first-line selective serotonin reuptake inhibitor (SSRI) class of antidepressants used for major depressive disorders. The cost to the patient for a prescription of 30 sertraline 100mg tablets (PBS item number 02237R) is AUD $19.78. An important consequence for this study to note is the information on under co-payment mental health-related medications was not collected before April 2012 under the 1953 National Health Act.[54] Antidepressants were affected by this change, with complete information for non-concession beneficiaries only available from 2012 onwards. Our study uses data only from 2012 onwards.

Two types of mental healthcare were analysed in this study: (i) referral for talking therapies through the 'Better Access Scheme'; and (ii) prescriptions for antidepressants. The Better Access Scheme provided at that time up to 10 subsidised services regardless of age and socioeconomic circumstances for the purposes of managing mental illness, including services delivered by, psychiatrists, psychologists, occupational therapists, social workers and general practitioners. Clinically-proven talking therapies are offered within this scheme for people diagnosed with a mental disorder(s) by a clinical expert. The items listed on the MBS are 80,000–80,170 (see Supplementary Table 1).

Secondly, we extracted the following classes of antidepressants from the PBS[55]: (i) selective serotonin reuptake inhibitors (SSRI); (ii) serotonin noradrenaline reuptake inhibitors (SNRI); (iii) tricyclic antidepressants (TCA); (iv) monoamine oxidase inhibitors (MAOI); and (v) other (e.g. mirtazapine and reboxetine). These items are listed in full in Supplementary Table 2. We restricted all analyses to records of antidepressant prescriptions and referrals for talking therapies between 2012 and 2016 to focus on the most comprehensive data available (given the issue with the reporting of antidepressants before 2012 in non-concessionary patients as outlined above). Therefore, records of mental healthcare prior to 2012 were not considered due to incomplete data. The following outcomes were generated:

1. **Prescription/referral:** three binary variables indicating whether a participant did/did not have at least one (i) course of antidepressants, (ii) referral for talking therapy, or (iii) a record of either one, hereafter referred to as 'combined'. Importantly, in this case neither a course of antidepressants nor a referral for talking therapy necessarily refers to a single tablet or meeting with a clinical psychologist, but courses of treatment of varying durations and costs charged. Furthermore, these records are of prescriptions dispensed and of referrals made, which does not equate directly to use of those medicines or the actual interaction with a clinical psychologist. Two sets of binary variables were constructed to distinguish between those participants who at some point received both types of healthcare, compared with those who received only one. The first set was labelled 'mutually exclusive' and referred to an outcome

measured in the absence of the other (e.g. at least one antidepressant among a subset of participants with no referral for talking therapy). For purposes of checking the sensitivity of these results, a second set was called 'intersecting' and referred to an outcome measured regardless of the other (e.g. at least one antidepressant regardless of referral for talking therapy).

2. **Counts of prescriptions/referrals**: Two variables were constructed to sum up the total courses of treatment involving (i) any type of antidepressants listed on the PBS, and (ii) talking therapies. A combined count variable was considered inappropriate as a course of antidepressants is not equivalent to a referral for a series of talking therapies with a clinical psychologist in quantitative terms. Moreover, talking therapy constituting a first line of treatment for mild to moderate mental illness, whereas antidepressants with/without talking therapies are considered the first line of treatment for moderate to severe and severe depression only, so differences in treatment patterns will to a large extent reflect the underlying diagnosis. Accordingly, these count outcomes were analysed separately by healthcare type, but no attempt was made to distinguish between courses of treatment which varied in duration.

3. **Healthcare costs**: Three healthcare cost variables were calculated: (i) cumulative 'fees charged' for antidepressants, talking therapies, and combined mental healthcare recorded for each participant in total; (ii) cumulative 'benefit' paid by the state towards mental healthcare recorded for each participant; and (iii) the cumulative 'contribution' (i.e. co-payment) paid by each participant. Two sets of these three cost variables were constructed. The first set reflected the total cost per year per participant and was calculated for antidepressants and talking therapy separately, as well as in combination. The second set reflected the mean cost per item per participant calculated for antidepressants and talking therapy separately only, divided by the count of each record type, respectively.

Statistical analysis and adjustment for confounding

The mental healthcare prescription and fee were described using frequencies, chi-square tests, means and standard errors in SAS Enterprise Guide software (Version 7.11). All models were fitted to test association with total green space availability as the primary exposure variable. A second set of models was then calculated to substitute separate measures of tree canopy and open grass for the total green space variable. All models were adjusted for confounding variables hypothesised to influence access to green space and mental health. These variables included age, sex, relationship status, annual household income (Australian dollars, before tax), highest educational qualification, and work status (e.g. employed, unemployed, retired). All models were fitted with random intercept based on areas. This was done by fitting multilevel models to account for the hierarchical data structure in which participants sharing areas were more likely to have similar health and other characteristics than their peers in other areas. The areas used were 'Statistical Area level 3', developed by the ABS to represent populations of 30 000 to 130 000 people in local government areas (council areas) and major transportation and commercial hubs. Model selection was outcome dependent, as follows:

1) Multilevel logistic regressions in MLwiN (v3.02)[56] using Markov Chain Monte Carlo (MCMC) estimation[57] were used to test associations between each green space variable and prescription of at least one course of antidepressants, referral for at least one session of talking therapy, or a combination of the two. Exposure time was used as a co-variate to adjust for length of follow-up.
2) Multilevel negative binomial regression (also in MLwiN) was used to examine association between each green space variable and counts of courses of antidepressants prescribed or referrals for talking therapy for each participant with a minimum of one prescription/referral. Length of follow up was adjusted with offsets.
3) Multilevel generalised linear model with gamma distribution in SAS software (Proc GLIMMIX) was used to estimate associations between each green space variable and each of the fee outcomes among participants with at least one prescription/referral record.

RESULTS

Description of prescribing and referral patterns within the sample

41,857 (75.6%) of the 55,339 participants had no record of any of the selected mental healthcare items listed on the MBS or PBS between 2012 and 2016. Prescription of at least one course of antidepressants occurred for 20.01% (n=11,071; Table 1). Referral for at least one session of talking therapy occurred in 8.95% (n=4,954). In total, 13,482 participants (24.4%) were prescribed or referred for at least one of the aforementioned treatments.

Referral for talking therapy was lower among participants with more green space availability overall. In contrast, antidepressant prescribing with respect to total green space available was less consistent. Proportionally fewer participants were consistently prescribed antidepressants and/or talking therapy where there was more tree canopy nearby. For example, 17.76% of participants with ≥30% tree canopy available were prescribed antidepressants, compared with 23.91% of those with 0-9% tree canopy. Referral for talking therapy was also proportionally slightly lower with more open grass availability, whereas antidepressant prescribing was higher (e.g. 25.12% where open grass availability was ≥20%, compared with 17.08% where open grass was <5%).

Antidepressant prescribing and referral for talking therapy were higher among females, participants not in relationships, and those who were not in paid employment. Antidepressant prescribing was higher, and referral for talking therapy lower, among older participants and retirees. Referral for talking therapy was higher, and antidepressant prescribing was lower, among participants with higher incomes and educational qualifications.

Odds of prescribing courses of antidepressants and/or referral for talking therapy

Adjusted odds ratios indicated positive association between a 10% increase in total green space availability was associated with OR=1.05 for antidepressant prescribing (95%CI=1.04-1.08; Figure 1, Supplementary Table 3 for the full sets of results including covariate parameters). The odds ratio for total green space and talking therapy referrals was not statistically significant (OR=0.97, 95%CI=0.94-1.01). The odds ratio for total green space and combined antidepressant medications and talking therapy referrals was also not statistically significant (OR=1.02, 95%CI=0.99-1.06).

Further analysis by green space type revealed divergent findings. None of the associations between tree canopy and the odds of receiving an antidepressant prescription or talking therapy referral reached statistical significance. A 10% increase in open grass was associated with 17% higher odds of being prescribed an antidepressant (OR=1.17, 95%CI=1.13-1.20) and 13% higher odds of either type of mental healthcare (OR=1.13, 95%CI=1.07-1.18), but also lower odds of referral for talking therapy (OR=0.87, 95%CI=0.82-0.92).

Counts of antidepressants prescribed and/or psychological counselling sessions

Results hereafter refer only to participants with at least one record of antidepressant prescribing (n=11,071) or attendance for psychological counselling (n=4,954) (prescription/referral n= 16,025) within the study period. Figure 2 (Supplementary Table 4 for full results) shows a 10% increase in green space was associated with higher incident rate ratio (IRR) of antidepressant prescription counts (IRR=1.02, 95%CI=1.00-1.04), but also lower IRR for referrals to talking therapy (IRR=0.97, 95%CI=0.95-0.99). Models focussed on green space type indicated positive association only between open grass and antidepressant prescribing counts (IRR=1.06, 95%CI=1.03-1.08). Lower IRR was observed between open grass and talking therapy referrals (IRR=0.93, 95%CI=0.90-0.96), with no association for tree canopy.

Total costs per year of antidepressant prescriptions and talking therapy referrals per item per participant

Figure 3 (also Supplementary Table 5) reports association between a 10% increase in green space availability and total costs per year for antidepressant prescriptions and talking therapy referrals per item per participant with respect to fees, benefits (i.e. state subsidy) and contributions (i.e. patient co-payment). A 10% increase in total green space availability was associated with higher total fees charged (Means Ratio (MR)=1.04, 95%CI=1.00-1.09) and total individuals contribution (MR=1.05, 95%CI=1.02-1.09) for antidepressant prescribing per participant after adjustment. Positive associations with were also observed for a 10% increase open grass with all three cost variables. A 10% increase in tree canopy was associated with total individuals contribution only (MR=1.04, 95%CI=1.01-1.08).

Associations observed for costs of talking therapy were different to those for antidepressants, with none of the associations between total green space availability and the cost of talking therapy reaching statistical significance. A 10% increase in open grass was associated with lower total costs (MR=0.92, 95%CI=0.5-0.98) and total individuals contribution (MR=0.90, 95%CI=0.83-0.97) for talking therapies. Like antidepressants, a 10% increase in tree canopy was also associated with higher total individuals contribution (MR=1.07, 95%CI=1.01-1.12).

When the costs of antidepressant prescriptions and talking therapy referrals were combined, statistically significant associations were observed only for total individuals contribution and a 10% increase in total green space (MR=1.041, 95%CI=1.01-1.07) and tree canopy (MR=1.05, 95%CI=1.01-1.09).

Mean costs of antidepressant prescriptions and talking therapy referrals per participant

Figure 3 (and Supplementary Table 5) also showed analysis of mean costs per participant (i.e. costs of antidepressants or talking therapy divided by the count of prescriptions or referrals). This analysis indicated that the results for the aforementioned total cost outcomes were mainly a function of differences in prescribing and referral frequencies. This was evident with statistically significant positive association between open grass and all cost variables, except for mean individual contribution for talking therapy referrals (which was still positively associated). Mean costs of antidepressant prescriptions and talking therapy referrals did not vary with respect to tree canopy. Total green space was only associated with mean fees for talking therapy referrals (MR=1.02, 95%CI=1.00-1.04).

Further analyses

Patterning of green space with respect to income and education were reported in Supplementary Table 6, with participants on higher incomes and/or with higher educational qualifications tending to have more tree canopy cover and less open grass nearby. We also conducted sensitivity analyses in this sample using logistic regressions and the Kessler 10 Psychological Distress Scale.[58] Previously reported associations[23] were replicated, wherein people with access to more tree canopy had lower, and open grass higher odds of experiencing psychological distress. Comparison was made between the analytical sample with participants living in Sydney, Newcastle and Wollongong at baseline (n=110,234). Supplementary Table 7 reports evidence of retention at follow-up of more affluent participants, in particular those with annual household incomes $\geq$\$70,000 per year. Finally, differences in the length of follow-up and mortality as a key factor determining follow-up time were both assessed with respect to each green space variable. Mortality data was linked using probabilistic methods by the Centre for Health Record Linkage (CHeReL, https://www.cherel.org.au/). Supplementary Table 8 reports no meaningful differences in the mean years of follow-up with respect to any of the green space variables. Levels of all-cause mortality were slightly lower in populations with $\geq$30% tree canopy compared with

<10% tree canopy (2.19% versus 2.74%, p=0.009). This may indicate that the results reported may not be impacted significantly by length of follow-up.

DISCUSSION

Summary of the main findings

We conducted the first person-level (i.e. non-ecological) study internationally to assess whether urban green space was associated with lower antidepressant prescribing, talking therapy referrals, and associated healthcare expenditure. Our results were contingent upon the type of green space. Unexpectedly, tree canopy was not associated with either mental healthcare or its costs, except for higher levels of patient contributions to overall costs. On the other hand, open grass was associated with lower odds of being referred for talking therapy, and lower total costs but also higher mean costs for talking therapy. Moreover, participants with more open grass tended to have higher odds of being prescribed antidepressants and higher total and mean per person costs for antidepressant prescriptions.

These unexpected results may provide pause for reflection on the validity of inferences and extrapolations commonly made from studies linking urban green space with better mental health to projected reductions in mental healthcare utilisation and associated expenditure. Hereafter, we structure our discussion to reflect on the absence of findings for tree canopy, the higher levels and costs of antidepressant prescribing with open grass, followed by a reflection on key strengths and limitations that give rise to future research directions.

On the absence of findings for tree canopy

The absence of association between tree canopy and antidepressant prescribing and talking therapy referrals was surprising, given previous research (including one paper using the 45 and Up Study) has reported lower odds of psychological distress and better general health in populations with more trees nearby.[23 39 40] These results also run counter to several ecological studies reporting lower levels of antidepressant prescribing[33 34] and lower Medicare costs in areas with more tree canopy.[38]

To a potentially large extent, the explanation for these null findings may lie with a lack of concordance between people in the community who are experiencing substantial mental ill-health that would warrant healthcare of the type analysed and those who actually receive it. Previous work has treated antidepressant medications as if they are an objective indicator of mental ill-health. However, it should be incumbent on those studies and others in future to acknowledge the inherent limitations of this position if there are known, or likely to be large numbers of people living with depression that is undiagnosed and untreated. More so, if antidepressants constitute one of many potential treatment options for depression, and especially if multiple indications for their prescribing are present (all of which potentially lead to substantial outcome misclassification).

In Australia, the mental healthcare data to which we have access is from provision and cost of a fee-for-service framework. Antidepressant prescribing is sensitive to factors including local detection practices and the availability of other treatment options (such as talking therapies) that influence the probability that a person with depression will receive them. In Australia, moderate-to-severe depression is the main indication for antidepressants, though they are sometimes also prescribed for so-called 'off-label' indications including chronic pain and urinary incontinence. Furthermore, these data tells us nothing about whether antidepressants dispensed were actually taken. For instance, a recent Australian study conducted using a different data source found approximately 20% of 146 elderly persons prescribed antidepressants did not self-report taking them.[55] Whether this reflects actual levels of usage, recall bias or a reticence towards disclosing use of antidepressants (e.g. due to a lack of felt safety and potential stigma) is unclear, but it is nonetheless indicative of the many challenges of using administrative prescription data to infer potential impacts of green space on mental health, health care and related expenditure.

On the higher levels of antidepressant prescribing and associated costs with open grass

Unlike the null findings for tree canopy, our other results are aligned with some previous studies that indicated evidence of potentially poorer levels of mental health with more open grass nearby, which in turn, could explain higher levels of antidepressant prescribing.[23 39] Higher total per person antidepressant expenditure with more open grass is likely to be attributable not only to higher frequencies of prescribing, but also higher per person mean costs of antidepressants. Concession card holders for pensions and people on lower incomes in Australia pay substantially lower contributions to the cost of antidepressant prescriptions. Although our analyses adjusted for age and multiple measures of socioeconomic circumstances including annual household income, lower levels of concession card holders in areas with more open grass (which analyses in this paper indicate tend to be more socioeconomically disadvantaged) may also contribute to this pattern.

But why might levels of mental ill-health and antidepressant prescribing be higher in areas with more open grass? These findings also align somewhat with previous work from the US indicating higher green space availability associated with higher all-cause and cardiovascular mortality at the city-scale.[59] Couple with those studies on mental health, [23 39] it is plausible that areas of cities with more open grass are less compact and more sprawling, instituting greater desire or necessity for motorised travel even for errands over shorter distances. In some cases these areas of open grass may be derelict and abandoned land that people select not to visit, perhaps due to concerns over safety, or represent aggregations of private gardens and golf courses walled off from view and inaccessible to the public. Such circumstances may result in communities that appear very green from above but lacking attractive or accessible public green space. Both circumstances may compound a lack of walkability and a majority reliance upon automobiles due to felt higher levels of convenience, privacy and autonomy in comparison with public and active transport options.[60] Thus, instead of more open grass leading to better mental health and lower mental healthcare expenditure, it may lead to less time in nature, more time in cars, higher risks of stress[61] and obesity,[62] and reduced participation in physical[63] and civic activities[64] known to support better mental health. Further work in this regard might consider interactions between different types of green space with levels of walkability, cycling infrastructure and public transport access points, as well as the issue of whether a green space is publically accessible and/or visible, or walled off from the public.

Strengths and limitations

A hitherto ignored issue in studies of green space and healthcare expenditure is the question of 'who pays?' This is relevant in countries such as Australia where the state subsidises, but does not necessarily fully cover the costs of healthcare. Our study provides first insight into this issue of equity, with covariate adjusted analysis showing higher individual contributions to costs of antidepressants by participants living in areas with more tree canopy. Individual contributions were also higher for antidepressants and lower for talking therapy among participants with more open grass. Consideration of expenditure on antidepressant prescribing and talking therapy referrals is another novel component of our study, given previous work linking green space with mental healthcare and associated expenditure has focussed almost exclusively on antidepressants.[33 34 37] This is important because research has shown that talking therapy, including but not limited to cognitive behavioural therapy, can be as efficacious for treating depression as antidepressant medications, and also reduce the risk of relapse.[65] Talking therapy and antidepressants may be used in tandem for treatment of moderate to severe depression, but many people experiencing minor forms distress may also seek, or be referred by a GP for talking therapy without any diagnosis of chronic depression. As such, talking therapy needs to be incorporated into any study of mental healthcare expenditure associated with green space to ensure potential costs (or savings) are not underestimated.

That said, our study is limited by a lack of data on costs associated with mental health ambulatory care hospitalisations and other aspects of healthcare expenditure affected by mental health (e.g. impacts of depression on diabetes treatment adherence[66]). Each of these constitute worthwhile avenues for future investigation to more comprehensively understand how green space may influence healthcare expenditure via mental health. Also, our study is also limited by age group. Data was only available on persons aged 45y or older, which means these results cannot be generalised to younger people, for whom interactions with green space and experiences with negotiating the healthcare system can be quite different. This is an important area for future research.

Our study has further limitations that warrant acknowledgement. While adjustment for income, education and employment status does help to address potential socioeconomic confounding in ways that were not possible in the ecological studies that have dominated thus far, this does not address disparities in wealth that may still influence access to green space and risk of mental ill-health. Although a legion of studies have reported mental health benefits of green space (e.g.[8 67-69]), and that work has been extended by examining different types of green space,[23 39 40] these remain fairly coarse definitions based on data from a single time point. Loss of green space may have occurred in some areas that cannot be taken into account. Meanwhile, changes in green space may also have occurred that influence experiential qualities of a neighbourhood; the look, feel and level of shade in a street lined with jacaranda trees may be quite different from one lined with palms. Similarly, the felt quality and/or state of disrepair may vary between two green spaces of equivalent size in consequential ways for whether people consider them safe places to relax, exercise and meet with neighbours.[70] Research has already shown associations between green space and mental health can be stronger when those green spaces are considered higher quality (e.g.[69 71 72]). How variations in green space quality might influence mental healthcare and associated expenditure remains under-researched, as is the potential intersection with changes in urban form and green space provision that may be closely entwined with wider trends in population growth, densification, local economy, and healthcare provision.

These are common limitations to all studies on green space and mental healthcare thus far and warrant further investigation, especially if the availability of green space not only influences need for mental healthcare, but also effects decisions with respect to how mental healthcare is administered. For instance, it may be that a nearby woodland or botanic garden can be a preferential setting for implementation of some non-pharmaceutical forms of mental healthcare, such as so-called ‘nature prescriptions’ (or ‘green social prescriptions’). Although many nature prescriptions have been implemented, there has been no randomised control trial to test their effectiveness or cost-effectiveness so far.[73] Further work designed to test whether investments in urban greening and health sector-oriented interventions that facilitate greater levels of green space visitation influence mental healthcare expenditure are worth pursuing.

Conclusions

Community greening strategies may well improve mental health among residents and this is a highly laudable goal with a substantial range of co-benefits. But at the same time, this study found individual-level covariate adjusted evidence of increased mental healthcare expenditure associated with urban greening, especially with respect to open grass. A range of complementary avenues for further investigation have been proposed, understanding that this study is among the first to assess association between different types of green space and actual expenditure from multiple forms of mental healthcare, with such analysis key to informing budget constrained healthy place making.

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Table 1: Frequencies and percentages for the three study outcomes by green space availability

	Total N	Antidepressants		Talking therapies		Combined	
		N	%	N	%	N	%
Overall	55,339	11,071	20.01	4,954	8.95	13,482	24.36
Total green space							
0-24.9%	7,172	1,353	18.87	737	10.28	1,752	24.43
25.0-31.9%	9,370	1,732	18.48	836	8.92	2,152	22.97
32.0-39.9%	12,397	2,499	20.16	1,087	8.77	3,013	24.30
40.0-49.9%	14,898	3,194	21.44	1,300	8.73	3,771	25.31
≥50.0%	11,502	2,293	19.94	994	8.64	2,794	24.29
Chi-square (p-value)		38.7	**P≤0.001**	18.2	**P≤0.001**	17.3	**P≤0.001**
Trees canopy							
0-9.9%	5,829	1,394	23.91	525	9.01	1,602	27.48
10.0-19.9%	21,301	4,443	20.86	2,036	9.56	5,403	25.37
20.0-29.9%	14,064	2,722	19.35	1,216	8.65	3,324	23.63
≥30.0%	14,145	2,512	17.76	1,177	8.32	3,153	22.29
Chi-square (p-value)		113.7	**P≤0.001**	18.2	**P≤0.001**	79.4	**P≤0.001**
Grass area							
0-4.9%	6,927	1,183	17.08	658	9.50	1,571	22.68
5.0-9.9%	23,124	4,167	18.02	2,026	8.76	5,226	22.60
10.0-19.9%	14,158	2,925	20.66	1,265	8.93	3,512	24.81
≥20.0%	11,130	2,796	25.12	1,005	9.03	3,173	28.51
Chi-square (p-value)		279.8	**P≤0.001**	3.7	P=0.300	155.0	**P≤0.001**
Age							
45-64 y	26,955	4,907	18.20	3,346	12.41	6,625	24.58
65-74 y	16,515	3,364	20.37	1,145	6.93	3,891	23.56
75-84 y	7,745	1,866	24.09	362	4.67	1,995	25.76
≥85 y	4,124	934	22.65	101	2.45	971	23.55
Chi-square (p-value)		154.9	**P≤0.001**	866.7	**P≤0.001**	16.1	**P≤0.001**
Sex							
Male	25,498	3,845	15.08	1,531	6.00	4,651	18.24
Female	29,841	7,226	24.22	3,423	11.47	8,831	29.59
Chi-square (p-value)		717.0	**P≤0.001**	504.1	**P≤0.001**	961.7	**P≤0.001**
Household income (AUD $)							
0-$29,999	10,396	3,006	28.9	932	9.0	3,320	31.9
$30,000-$69,999	15,956	3,231	20.2	1,388	8.7	3,894	24.4
≥ $70,000	18,490	2,747	14.9	1,777	9.6	3,763	20.4
Missing	10,497	2,087	19.9	857	8.2	2,505	23.9
Chi-square (p-value)		821.6	**P≤0.001**	9.1	**P≤0.001**	483.1	**P≤0.001**
***Educational**							
None	3,389	1,023	30.2	257	7.6	1,101	32.5
School	31,783	6,746	21.2	2,690	8.5	7,993	25.1
University	19,652	3,169	16.1	1,966	10.0	4,240	21.6
Missing	515	133	25.8	41	8.0	148	28.7
Chi-square (p-value)		434.7	**P≤0.001**	43.7	**P≤0.001**	215.1	**P≤0.001**
Work status							
Working	24,953	3,891	15.6	2,666	10.7	5,391	21.6
Retired	25,907	5,770	22.3	1,722	6.6	6,495	25.1
Other	3,738	1,219	32.6	527	14.1	1,388	37.1
Missing	741	191	25.8	39	5.3	208	28.1
Chi-square (p-value)		759.9	**P≤0.001**	380.1	**P≤0.001**	441.4	**P≤0.001**
Relationship status							
Yes	41,331	7,624	18.4	3,254	7.9	9,257	22.4
No	13,444	3,315	24.7	1,641	12.2	4,057	30.2
Missing	564	132	23.4	59	10.5	168	29.8
Chi-square (p-value)		244.9	**P≤0.001**	234.1	**P≤0.001**	333.7	**P≤0.001**

Combined refers to at least one antidepressant prescribed or talking therapy referral without distinction by healthcare type

Figure 1: Multilevel logistic regressions for assessment of associations between 10% increase in green space, tree canopy and open grass, with prescription of antidepressant medications and/or referral for talking therapies, adjusted for potential confounding

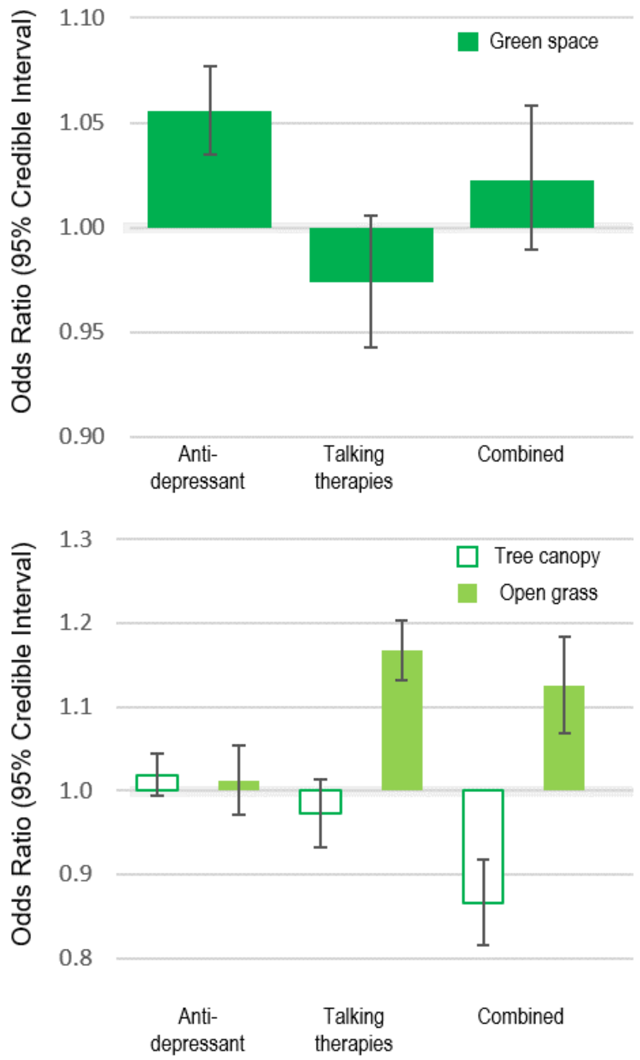


Figure 2: Multilevel negative binomial regressions for assessment of associations between 10% increase in green space, tree canopy and open grass, with counts of prescriptions of antidepressant medications and/or referrals for talking therapies, adjusted for potential confounding and discounting participants with no record of antidepressant prescription or referral for talking therapy

Need more comments to say there are 4 mods, see Table S4

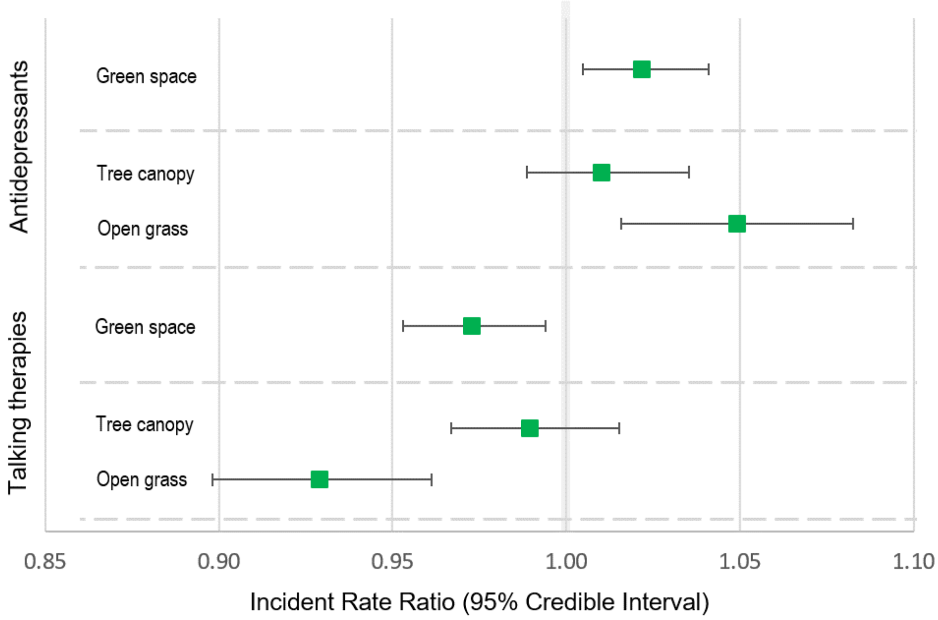
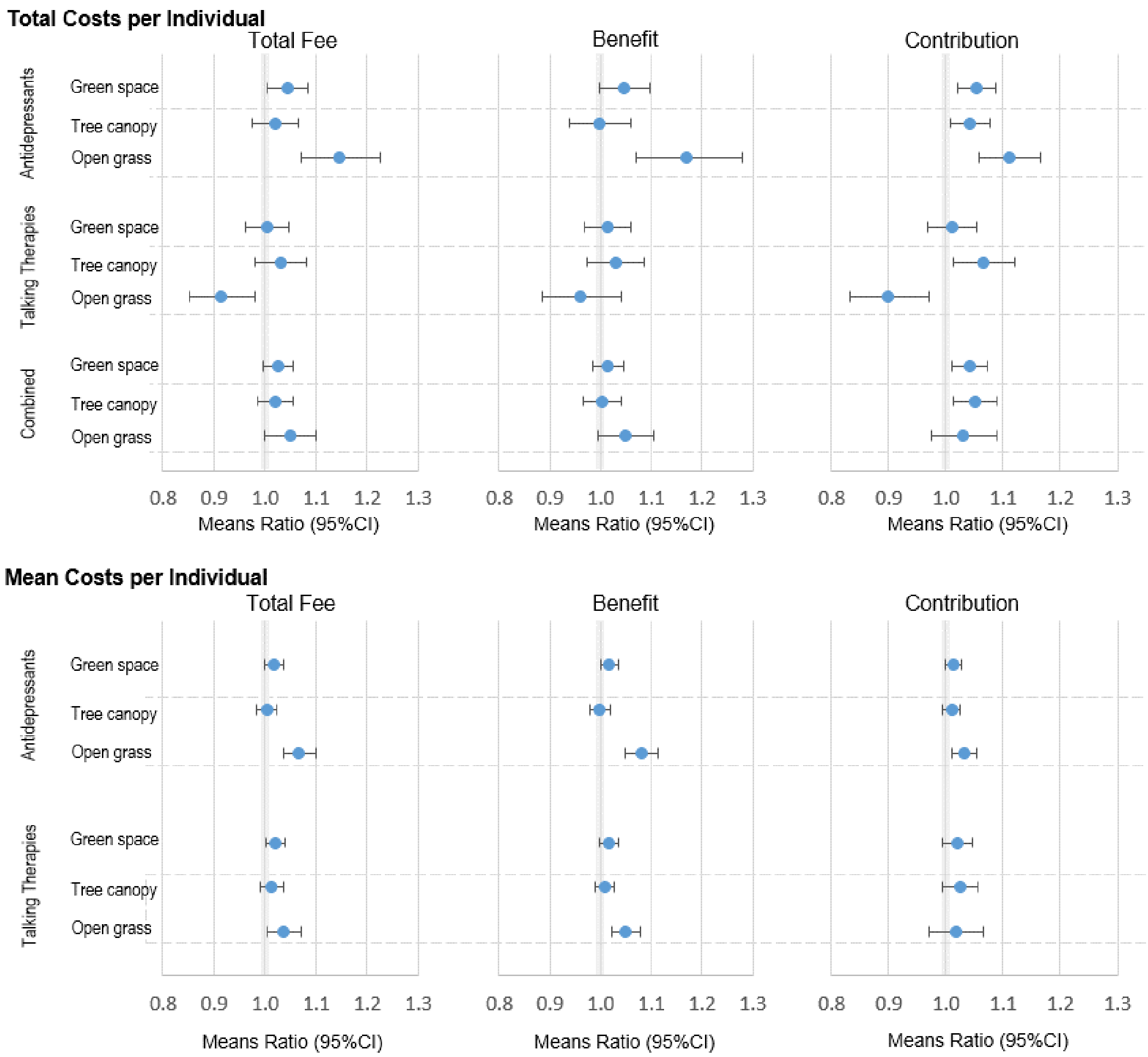


Figure 3: Multilevel generalised linear models with gamma distribution for assessment of associations between 10% increase in green space, tree canopy and open grass, with fees of prescriptions of antidepressant medications and/or referrals for talking therapies, adjusted for potential confounding and discounting participants with no record of antidepressant prescription or referral for talking therapy



Is urban green space associated with lower mental healthcare expenditure?

INTRODUCTION

Over 70% of the world's population is expected to live in cities by the year 2050.[1] The shift in planning away from sprawling low density metropolises to increasingly compact cities through processes of urban regeneration and in-fill housing has strong public health support.[2 3] But this shift also provokes unease among some conservationists, urban planners, landscape architects and others concerned with losses in biodiversity and urban green space.[4 5] Globally, people advocate for investment in urban green space and tree canopy [6] by claiming it will help to avert the climate crisis, mitigate water shortages, prevent a sixth mass extinction, improve liveability and strengthen community health.[7-9] A key component of this advocacy is a purported reduction in healthcare expenditure. For example, Public Health England's "Improving access to green space: A new review for 2020" report[10] claimed *"£2.1 billion per year could be saved in health fees if everyone in England had good access to greenspace…"* (pp.12).

Meta-analyses of experimental and epidemiological studies indicate evidence for urban green spaces providing opportunities for stress relief[11] and renewal of depleted cognitive capacities for optimal executive functioning.[12 13] This *'restoration'* pathway is based on established theories of stress reduction[14 15] and attention restoration.[16 17] Restoration and stress reduction are highly related to human behaviour that helps to build health capacities, such as social interaction and physical activity. A third pathway is the extent to which urban greening may provide community-wide reductions in ambient hazards, such as temperature cooling,[18] air quality filtering[19] and buffering of excess noise.[20] Together, these pathways may lower the risk of non-communicable diseases[21] and premature death.[22] Accordingly, one might hypothesise that the health benefits accrued by populations resident in areas with more green space will translate into reduced healthcare use and lower levels of health expenditure.

While the evidence for investing in green space for health benefit increases (e.g. our work in Australian cities indicate restoring urban tree canopy to ≥30% of local land-use are associated with reduced levels of incident psychological distress,[23] cardiometabolic diseases,[24] and dementia[25]), it is rare for claims of reduced healthcare expenditure to be based upon analysis of actual healthcare use. In most studies estimates are based on projections,[26] quality-adjusted life years[27 28] or 'value of statistical life'.[29] Analysis of actual healthcare data is critically important to understand the true relative costs involved and who is bearing them. We know that many people who need healthcare do not receive it[30] so investment in green space as an adjunct to formal healthcare is an appealing hypothesis.[31] Conversely however, increased longevity may result in *increased* healthcare use and fees.[32] In many countries a patient co-payment is required for certain types of healthcare (e.g. medications). The question of 'who pays?' adds an equity dimension that has been previously ignored.

Some researchers have focussed on prescribing patterns in healthcare without analysing costs when determining the impact of green space. Reductions in dispensing of antidepressant medication was found within municipalities in the Netherlands where total green space reached 28% land-cover or greater,[33] and in boroughs in London (UK) with higher street tree density.[34] Lower odds of antidepressant prescribing were observed with more street trees but only among people in less favourable socioeconomic circumstances in a German study.[35] In Spain, a study reported lower odds of self-reported antidepressants by people in greener neighbourhoods.[36] In contrast, a study spanning the whole of England reported no difference in antidepressant prescribing in neighbourhoods with more green space, but there were *higher* rates of prescribing and spending on cardiovascular medications.[37] Mixed results have also been found in the US, with less Medicare spending seen in counties with more forest and shrub, but not in counties with more agricultural land, urban vegetation or grass cover.[38]

Several questions remain unanswered. Do the reductions in antidepressant prescribing indicate less need for antidepressants due to better population mental health, or perhaps an inability of individuals to afford the consultation fee and/or costs of antidepressants prescribed in contexts where medications are not covered by universal healthcare? While both scenarios assume cost-savings, one is indicative of benefit and the other of potential harm. Furthermore, does the type of green space matter? This is pertinent to ask given several of the aforementioned studies reported lower antidepressant prescribing and/or lower Medicare costs in areas specifically with more tree canopy,[34 35 38] but the US study not finding comparable results for areas with more open grass. Previous work has reported contrasting associations between these types of green space and indicators of mental health. More favourable mental health has been reported among populations with more tree canopy nearby, but with null or worse outcomes with more open grass,[23 39 40] indicating the potential for flow-on impacts and contrasting associations with mental healthcare use and costs.

Limited and conflicting cost analyses indicate a need for research specifically designed to determine whether urban greening strategies can lead to reduced healthcare expenditure. An important current limitation of all previous studies using healthcare claims data to assess association with green space is that they have been ecological and susceptible to ecological fallacy (the mistaken assumption that associations observed at a group or population level always apply at the individual level[41]) and to biases related to scale and the modifiable areal unit problem (different ways of delineating area boundaries can manipulate data aggregation to confound direction and magnitude of associations).[42 43] A lack of adjustment for individual-level socioeconomic circumstances in ecological studies may leave studies vulnerable to residual confounding given various studies reporting more affluent groups tending to have access to more green space.[25 44 45] Further, this lack of adjustment may have other implications for model validity of samples within countries where healthcare access is strongly dependent upon income, educational attainment and employment, especially where universal healthcare coverage is absent or does not cover all healthcare costs.

We analysed associations between different types of green space and per-person expenditure on mental healthcare recorded in a large sample of individuals resident in three Australian cities. Use of individual-level data permitted adjustment for a range of potential socioeconomic confounders including income, education and employment status, eliminating the limitations of previous ecological studies. Given reported loss of contact with green space in urban areas and links between green space and mental health within rural areas being potentially bound up with contextual issues such as agricultural pesticide use[46] and drought,[47] our focus was on residents in the cities of Sydney, Newcastle and Wollongong, the three largest cities in the Australian state of New South Wales (NSW). We further contrasted patterns of association with two types of mental healthcare (prescribing of antidepressant medications and referral for talking therapy) along with their relative costs to society and, where applicable, co-payments made by individuals, to quantify potential impacts on equity.

METHODS

Data

Participants in the Sax Institute's 45 and Up Study[48] were recruited between 2006 and 2009 from residents of NSW. People aged 45 years or older listed in the Services Australia (formerly the Department of Human Services) enrolment database (Australia's universal healthcare system, available to Australian and New Zealand citizens residing in Australia, as well as permanent residents in Australia and people from other selected countries[49]). Interested participants completed a questionnaire, resulting in an 18% response rate and a baseline sample of 267,153 people with a demographic profile that was broadly representative of the population aged $\geq$45 years in Australia.[50] Participants in our study were selected from the second full follow-up wave (N=141,014) recruited between 2012 and 2015.

Supplementary figure 1 reports the derivation of the analytical sample of 55,339. In brief, a total of 55,388 participants were retained from the 141,014 follow-up sample as they were residing in one of Sydney, Newcastle or Wollongong (omitting 85,626 living in other areas of NSW). A further 49 participants were omitted as they had opted to withdraw their participation in the 45 and Up Study, reducing the sample from 55,388 to the final analytical sample of 55,339. Participants were censored at December 31st 2016 or earlier in the case of death. Records of death were ascertained via probabilistic linkage to the NSW Register for Births, Marriages and Deaths performed by the Centre for Health Record Linkage (https://www.cherel.org.au/). The average time observed for each participant between completion of the follow-up survey and either death or censoring was 4.97 years (0.8 min, 5.0 max).

The 45 and Up Study received ethics approval from the UNSW Human Research Ethics Committee (HREC). This study was approved by the University of Wollongong HREC and the NSW Population and Health Services Research Committee. Participants in the 45 and Up Study provided written informed consent for their responses to be linked to other data sources for the purposes of research.

Linkage to green space variables

The centroid of the 'Mesh Block' in which each participant resided was used as a proxy for their home address. Mesh Blocks are created by the Australian Bureau of Statistics (ABS) and are very small in both geographic area and in population, containing between 30 and 60 dwellings. Larger Mesh Blocks denoting inland water bodies, parklands, hospitals, industrial zones and educational precincts can be substantially larger, but these were not used as proxies for home addresses as they are not typically occupied. A 1.6km road network distance was used to create catchment areas for each participant, within which the percentage of land-use covered in green space was calculated. The 1.6 km distance was selected based upon published guidance around travel distances by foot[51] to capture cumulative opportunities for contact with green space near the home.[52] Green space was measured using 2-m raster surface land-use data acquired from Pitney Bowes Ltd for 2016 ('Geovision'). These data permitted calculation of three green space variables inclusive of private (e.g. gardens, back yards) or public (e.g. parks and reserves) land-use:

1. Percentage total green space, including tree canopy, open grass, and shrub
2. Percentage tree canopy, including deciduous and evergreen trees;
3. Percentage open grass that was not under tree canopy.

For descriptive purposes, each of these green space variables were stratified into categories aligned with peaks in distributions (close to arithmetic or geometric intervals), and planning standards for green space already in use (e.g. 10% of subdivisible land is allocated to green space in Perth, Western Australia[53]). The categories were: (i) total green space = 0-24.9%, 25.0-31.9%, 32.0-39.9%, 40.0-49.9%, $\geq$50.0%; (ii) tree canopy = 0-9.9%, 10.0-19.9%, 20.0-29.9%, $\geq$30.0%; (iii) open grass = 0-4.9%, 5.0-9.9%, 10.0-19.9%, $\geq$20.0%. Statistical analyses involved estimating associations for a putative 10% increase in each green space variable, using original continuous variable divided by 10. Shrub was not analysed as a separate type of green space because (i) it constitutes a minority land-use that may not be open to human interaction, (ii) urban greening policies tend to focus on tree planting and/or conservation of grassy areas conducive to sports and recreation, and (iii) open grass and tree canopy variables were fitted into models simultaneously, shrub omission avoids multicollinearity.

Outcome variable selection and implications for the analytical sample

Deterministic methods were used by the Sax Institute to link participant responses to records of mental healthcare prescription and fees listed on the Medicare Benefits Schedule (MBS) and Pharmaceutical Benefits Scheme (PBS) up to December 31st 2016 received from Services Australia. The MBS and PBS comprise lists of medical services and prescription medicines for which a rebate (i.e. 'benefit') is paid by the Australian Government to provide financial assistance towards the overall medical fee. It warrants noting that all Medicare Card holders irrespective of socioeconomic circumstances receive the full subsidy on prescriptions listed on the PBS and on referrals listed on the MBS. However, there can still be a charge for the patient depending upon the healthcare received. For example, on the MBS, the state covers 100% of the fee for consulting a GP. But the state covered 85% (AUD $129.55; 2021 costs) of the AUD $152.40 referral fee by a GP to a registered clinical psychologist for a minimum of 50 minutes for psychological assessment and therapy for a mental disorder (MBS item number 80010). In this case, the remaining 15% of the fee would form a co-payment paid by the patient (hereafter referred to as a 'contribution').

The PBS subsidises medications costing more than AUD $41.30 per prescription, with general patients will paying no more than this amount and concessionaries (pensioners, health care card holders, Commonwealth seniors health card holders and veterans card holders) paying no more than AUD $6.60. In cases where the dispensed cost of a medication is below AUD $41.30, the subsidy does not apply and non-concessionary patients are required to contribute the full cost (i.e. 'under co-payment'). For example, sertraline hydrochloride is among the first-line selective serotonin reuptake inhibitor (SSRI) class of antidepressants used for major depressive disorders. The cost to the patient for a prescription of 30 sertraline 100mg tablets (PBS item number 02237R) is AUD $19.78. An important consequence for this study to note is the information on under co-payment mental health-related medications was not collected before April 2012 under the 1953 National Health Act.[54] Antidepressants were affected by this change, with complete information for non-concession beneficiaries only available from 2012 onwards. Our study uses data only from 2012 onwards.

Two types of mental healthcare were analysed in this study: (i) referral for talking therapies through the 'Better Access Scheme'; and (ii) prescriptions for antidepressants. The Better Access Scheme provided at that time up to 10 subsidised services regardless of age and socioeconomic circumstances for the purposes of managing mental illness, including services delivered by, psychiatrists, psychologists, occupational therapists, social workers and general practitioners. Clinically-proven talking therapies are offered within this scheme for people diagnosed with a mental disorder(s) by a clinical expert. The items listed on the MBS are 80,000–80,170 (see Supplementary Table 1).

Secondly, we extracted the following classes of antidepressants from the PBS[55]: (i) selective serotonin reuptake inhibitors (SSRI); (ii) serotonin noradrenaline reuptake inhibitors (SNRI); (iii) tricyclic antidepressants (TCA); (iv) monoamine oxidase inhibitors (MAOI); and (v) other (e.g. mirtazapine and reboxetine). These items are listed in full in Supplementary Table 2. We restricted all analyses to records of antidepressant prescriptions and referrals for talking therapies between 2012 and 2016 to focus on the most comprehensive data available (given the issue with the reporting of antidepressants before 2012 in non-concessionary patients as outlined above). Therefore, records of mental healthcare prior to 2012 were not considered due to incomplete data. The following outcomes were generated:

1. **Prescription/referral:** three binary variables indicating whether a participant did/did not have at least one (i) course of antidepressants, (ii) referral for talking therapy, or (iii) a record of either one, hereafter referred to as 'combined'. Importantly, in this case neither a course of antidepressants nor a referral for talking therapy necessarily refers to a single tablet or meeting with a clinical psychologist, but courses of treatment of varying durations and costs charged. Furthermore, these records are of prescriptions dispensed and of referrals made, which does not equate directly to use of those medicines or the actual interaction with a clinical psychologist. Two sets of binary variables were constructed to distinguish between those participants who at some point received both types of healthcare, compared with those who received only one. The first set was labelled 'mutually exclusive' and referred to an outcome

measured in the absence of the other (e.g. at least one antidepressant among a subset of participants with no referral for talking therapy). For purposes of checking the sensitivity of these results, a second set was called 'intersecting' and referred to an outcome measured regardless of the other (e.g. at least one antidepressant regardless of referral for talking therapy).

2. **Counts of prescriptions/referrals**: Two variables were constructed to sum up the total courses of treatment involving (i) any type of antidepressants listed on the PBS, and (ii) talking therapies. A combined count variable was considered inappropriate as a course of antidepressants is not equivalent to a referral for a series of talking therapies with a clinical psychologist in quantitative terms. Moreover, talking therapy constituting a first line of treatment for mild to moderate mental illness, whereas antidepressants with/without talking therapies are considered the first line of treatment for moderate to severe and severe depression only, so differences in treatment patterns will to a large extent reflect the underlying diagnosis. Accordingly, these count outcomes were analysed separately by healthcare type, but no attempt was made to distinguish between courses of treatment which varied in duration.

3. **Healthcare costs**: Three healthcare cost variables were calculated: (i) cumulative 'fees charged' for antidepressants, talking therapies, and combined mental healthcare recorded for each participant in total; (ii) cumulative 'benefit' paid by the state towards mental healthcare recorded for each participant; and (iii) the cumulative 'contribution' (i.e. co-payment) paid by each participant. Two sets of these three cost variables were constructed. The first set reflected the total cost per year per participant and was calculated for antidepressants and talking therapy separately, as well as in combination. The second set reflected the mean cost per item per participant calculated for antidepressants and talking therapy separately only, divided by the count of each record type, respectively.

Statistical analysis and adjustment for confounding

The mental healthcare prescription and fee were described using frequencies, chi-square tests, means and standard errors in SAS Enterprise Guide software (Version 7.11). All models were fitted to test association with total green space availability as the primary exposure variable. A second set of models was then calculated to substitute separate measures of tree canopy and open grass for the total green space variable. All models were adjusted for confounding variables hypothesised to influence access to green space and mental health. These variables included age, sex, relationship status, annual household income (Australian dollars, before tax), highest educational qualification, and work status (e.g. employed, unemployed, retired). All models were fitted with random intercept based on areas. This was done by fitting multilevel models to account for the hierarchical data structure in which participants sharing areas were more likely to have similar health and other characteristics than their peers in other areas. The areas used were 'Statistical Area level 3', developed by the ABS to represent populations of 30 000 to 130 000 people in local government areas (council areas) and major transportation and commercial hubs. Model selection was outcome dependent, as follows:

1) Multilevel logistic regressions in MLwiN (v3.02)[56] using Markov Chain Monte Carlo (MCMC) estimation[57] were used to test associations between each green space variable and prescription of at least one course of antidepressants, referral for at least one session of talking therapy, or a combination of the two. Exposure time was used as a co-variate to adjust for length of follow-up.
2) Multilevel negative binomial regression (also in MLwiN) was used to examine association between each green space variable and counts of courses of antidepressants prescribed or referrals for talking therapy for each participant with a minimum of one prescription/referral. Length of follow up was adjusted with offsets.
3) Multilevel generalised linear model with gamma distribution in SAS software (Proc GLIMMIX) was used to estimate associations between each green space variable and each of the fee outcomes among participants with at least one prescription/referral record.

RESULTS

Description of prescribing and referral patterns within the sample

41,857 (75.6%) of the 55,339 participants had no record of any of the selected mental healthcare items listed on the MBS or PBS between 2012 and 2016. Prescription of at least one course of antidepressants occurred for 20.01% (n=11,071; Table 1). Referral for at least one session of talking therapy occurred in 8.95% (n=4,954). In total, 13,482 participants (24.4%) were prescribed or referred for at least one of the aforementioned treatments.

Referral for talking therapy was lower among participants with more green space availability overall. In contrast, antidepressant prescribing with respect to total green space available was less consistent. Proportionally fewer participants were consistently prescribed antidepressants and/or talking therapy where there was more tree canopy nearby. For example, 17.76% of participants with ≥30% tree canopy available were prescribed antidepressants, compared with 23.91% of those with 0-9% tree canopy. Referral for talking therapy was also proportionally slightly lower with more open grass availability, whereas antidepressant prescribing was higher (e.g. 25.12% where open grass availability was ≥20%, compared with 17.08% where open grass was <5%).

Antidepressant prescribing and referral for talking therapy were higher among females, participants not in relationships, and those who were not in paid employment. Antidepressant prescribing was higher, and referral for talking therapy lower, among older participants and retirees. Referral for talking therapy was higher, and antidepressant prescribing was lower, among participants with higher incomes and educational qualifications.

Odds of prescribing courses of antidepressants and/or referral for talking therapy

Adjusted odds ratios indicated positive association between a 10% increase in total green space availability was associated with OR=1.05 for antidepressant prescribing (95%CI=1.04-1.08; Figure 1, Supplementary Table 3 for the full sets of results including covariate parameters). The odds ratio for total green space and talking therapy referrals was not statistically significant (OR=0.97, 95%CI=0.94-1.01). The odds ratio for total green space and combined antidepressant medications and talking therapy referrals was also not statistically significant (OR=1.02, 95%CI=0.99-1.06).

Further analysis by green space type revealed divergent findings. None of the associations between tree canopy and the odds of receiving an antidepressant prescription or talking therapy referral reached statistical significance. A 10% increase in open grass was associated with 17% higher odds of being prescribed an antidepressant (OR=1.17, 95%CI=1.13-1.20) and 13% higher odds of either type of mental healthcare (OR=1.13, 95%CI=1.07-1.18), but also lower odds of referral for talking therapy (OR=0.87, 95%CI=0.82-0.92).

Counts of antidepressants prescribed and/or psychological counselling sessions

Results hereafter refer only to participants with at least one record of antidepressant prescribing (n=11,071) or attendance for psychological counselling (n=4,954) (prescription/referral n= 16,025) within the study period. Figure 2 (Supplementary Table 4 for full results) shows a 10% increase in green space was associated with higher incident rate ratio (IRR) of antidepressant prescription counts (IRR=1.02, 95%CI=1.00-1.04), but also lower IRR for referrals to talking therapy (IRR=0.97, 95%CI=0.95-0.99). Models focussed on green space type indicated positive association only between open grass and antidepressant prescribing counts (IRR=1.06, 95%CI=1.03-1.08). Lower IRR was observed between open grass and talking therapy referrals (IRR=0.93, 95%CI=0.90-0.96), with no association for tree canopy.

Total costs per year of antidepressant prescriptions and talking therapy referrals per item per participant

Figure 3 (also Supplementary Table 5) reports association between a 10% increase in green space availability and total costs per year for antidepressant prescriptions and talking therapy referrals per item per participant with respect to fees, benefits (i.e. state subsidy) and contributions (i.e. patient co-payment). A 10% increase in total green space availability was associated with higher total fees charged (Means Ratio (MR)=1.04, 95%CI=1.00-1.09) and total individuals contribution (MR=1.05, 95%CI=1.02-1.09) for antidepressant prescribing per participant after adjustment. Positive associations with were also observed for a 10% increase open grass with all three cost variables. A 10% increase in tree canopy was associated with total individuals contribution only (MR=1.04, 95%CI=1.01-1.08).

Associations observed for costs of talking therapy were different to those for antidepressants, with none of the associations between total green space availability and the cost of talking therapy reaching statistical significance. A 10% increase in open grass was associated with lower total costs (MR=0.92, 95%CI=0.5-0.98) and total individuals contribution (MR=0.90, 95%CI=0.83-0.97) for talking therapies. Like antidepressants, a 10% increase in tree canopy was also associated with higher total individuals contribution (MR=1.07, 95%CI=1.01-1.12).

When the costs of antidepressant prescriptions and talking therapy referrals were combined, statistically significant associations were observed only for total individuals contribution and a 10% increase in total green space (MR=1.041, 95%CI=1.01-1.07) and tree canopy (MR=1.05, 95%CI=1.01-1.09).

Mean costs of antidepressant prescriptions and talking therapy referrals per participant

Figure 3 (and Supplementary Table 5) also showed analysis of mean costs per participant (i.e. costs of antidepressants or talking therapy divided by the count of prescriptions or referrals). This analysis indicated that the results for the aforementioned total cost outcomes were mainly a function of differences in prescribing and referral frequencies. This was evident with statistically significant positive association between open grass and all cost variables, except for mean individual contribution for talking therapy referrals (which was still positively associated). Mean costs of antidepressant prescriptions and talking therapy referrals did not vary with respect to tree canopy. Total green space was only associated with mean fees for talking therapy referrals (MR=1.02, 95%CI=1.00-1.04).

Further analyses

Patterning of green space with respect to income and education were reported in Supplementary Table 6, with participants on higher incomes and/or with higher educational qualifications tending to have more tree canopy cover and less open grass nearby. We also conducted sensitivity analyses in this sample using logistic regressions and the Kessler 10 Psychological Distress Scale.[58] Previously reported associations[23] were replicated, wherein people with access to more tree canopy had lower, and open grass higher odds of experiencing psychological distress. Comparison was made between the analytical sample with participants living in Sydney, Newcastle and Wollongong at baseline (n=110,234). Supplementary Table 7 reports evidence of retention at follow-up of more affluent participants, in particular those with annual household incomes $\geq$\$70,000 per year. Finally, differences in the length of follow-up and mortality as a key factor determining follow-up time were both assessed with respect to each green space variable. Mortality data was linked using probabilistic methods by the Centre for Health Record Linkage (CHeReL, https://www.cherel.org.au/). Supplementary Table 8 reports no meaningful differences in the mean years of follow-up with respect to any of the green space variables. Levels of all-cause mortality were slightly lower in populations with $\geq$30% tree canopy compared with

<10% tree canopy (2.19% versus 2.74%, p=0.009). This may indicate that the results reported may not be impacted significantly by length of follow-up.

DISCUSSION

Summary of the main findings

We conducted the first person-level (i.e. non-ecological) study internationally to assess whether urban green space was associated with lower antidepressant prescribing, talking therapy referrals, and associated healthcare expenditure. Our results were contingent upon the type of green space. Unexpectedly, tree canopy was not associated with either mental healthcare or its costs, except for higher levels of patient contributions to overall costs. On the other hand, open grass was associated with lower odds of being referred for talking therapy, and lower total costs but also higher mean costs for talking therapy. Moreover, participants with more open grass tended to have higher odds of being prescribed antidepressants and higher total and mean per person costs for antidepressant prescriptions.

These unexpected results may provide pause for reflection on the validity of inferences and extrapolations commonly made from studies linking urban green space with better mental health to projected reductions in mental healthcare utilisation and associated expenditure. Hereafter, we structure our discussion to reflect on the absence of findings for tree canopy, the higher levels and costs of antidepressant prescribing with open grass, followed by a reflection on key strengths and limitations that give rise to future research directions.

On the absence of findings for tree canopy

The absence of association between tree canopy and antidepressant prescribing and talking therapy referrals was surprising, given previous research (including one paper using the 45 and Up Study) has reported lower odds of psychological distress and better general health in populations with more trees nearby.[23 39 40] These results also run counter to several ecological studies reporting lower levels of antidepressant prescribing[33 34] and lower Medicare costs in areas with more tree canopy.[38]

To a potentially large extent, the explanation for these null findings may lie with a lack of concordance between people in the community who are experiencing substantial mental ill-health that would warrant healthcare of the type analysed and those who actually receive it. Previous work has treated antidepressant medications as if they are an objective indicator of mental ill-health. However, it should be incumbent on those studies and others in future to acknowledge the inherent limitations of this position if there are known, or likely to be large numbers of people living with depression that is undiagnosed and untreated. More so, if antidepressants constitute one of many potential treatment options for depression, and especially if multiple indications for their prescribing are present (all of which potentially lead to substantial outcome misclassification).

In Australia, the mental healthcare data to which we have access is from provision and cost of a fee-for-service framework. Antidepressant prescribing is sensitive to factors including local detection practices and the availability of other treatment options (such as talking therapies) that influence the probability that a person with depression will receive them. In Australia, moderate-to-severe depression is the main indication for antidepressants, though they are sometimes also prescribed for so-called 'off-label' indications including chronic pain and urinary incontinence. Furthermore, these data tells us nothing about whether antidepressants dispensed were actually taken. For instance, a recent Australian study conducted using a different data source found approximately 20% of 146 elderly persons prescribed antidepressants did not self-report taking them.[55] Whether this reflects actual levels of usage, recall bias or a reticence towards disclosing use of antidepressants (e.g. due to a lack of felt safety and potential stigma) is unclear, but it is nonetheless indicative of the many challenges of using administrative prescription data to infer potential impacts of green space on mental health, health care and related expenditure.

On the higher levels of antidepressant prescribing and associated costs with open grass

Unlike the null findings for tree canopy, our other results are aligned with some previous studies that indicated evidence of potentially poorer levels of mental health with more open grass nearby, which in turn, could explain higher levels of antidepressant prescribing.[23 39] Higher total per person antidepressant expenditure with more open grass is likely to be attributable not only to higher frequencies of prescribing, but also higher per person mean costs of antidepressants. Concession card holders for pensions and people on lower incomes in Australia pay substantially lower contributions to the cost of antidepressant prescriptions. Although our analyses adjusted for age and multiple measures of socioeconomic circumstances including annual household income, lower levels of concession card holders in areas with more open grass (which analyses in this paper indicate tend to be more socioeconomically disadvantaged) may also contribute to this pattern.

But why might levels of mental ill-health and antidepressant prescribing be higher in areas with more open grass? These findings also align somewhat with previous work from the US indicating higher green space availability associated with higher all-cause and cardiovascular mortality at the city-scale.[59] Couple with those studies on mental health, [23 39] it is plausible that areas of cities with more open grass are less compact and more sprawling, instituting greater desire or necessity for motorised travel even for errands over shorter distances. In some cases these areas of open grass may be derelict and abandoned land that people select not to visit, perhaps due to concerns over safety, or represent aggregations of private gardens and golf courses walled off from view and inaccessible to the public. Such circumstances may result in communities that appear very green from above but lacking attractive or accessible public green space. Both circumstances may compound a lack of walkability and a majority reliance upon automobiles due to felt higher levels of convenience, privacy and autonomy in comparison with public and active transport options.[60] Thus, instead of more open grass leading to better mental health and lower mental healthcare expenditure, it may lead to less time in nature, more time in cars, higher risks of stress[61] and obesity,[62] and reduced participation in physical[63] and civic activities[64] known to support better mental health. Further work in this regard might consider interactions between different types of green space with levels of walkability, cycling infrastructure and public transport access points, as well as the issue of whether a green space is publically accessible and/or visible, or walled off from the public.

Strengths and limitations

A hitherto ignored issue in studies of green space and healthcare expenditure is the question of 'who pays?' This is relevant in countries such as Australia where the state subsidises, but does not necessarily fully cover the costs of healthcare. Our study provides first insight into this issue of equity, with covariate adjusted analysis showing higher individual contributions to costs of antidepressants by participants living in areas with more tree canopy. Individual contributions were also higher for antidepressants and lower for talking therapy among participants with more open grass. Consideration of expenditure on antidepressant prescribing and talking therapy referrals is another novel component of our study, given previous work linking green space with mental healthcare and associated expenditure has focussed almost exclusively on antidepressants.[33 34 37] This is important because research has shown that talking therapy, including but not limited to cognitive behavioural therapy, can be as efficacious for treating depression as antidepressant medications, and also reduce the risk of relapse.[65] Talking therapy and antidepressants may be used in tandem for treatment of moderate to severe depression, but many people experiencing minor forms distress may also seek, or be referred by a GP for talking therapy without any diagnosis of chronic depression. As such, talking therapy needs to be incorporated into any study of mental healthcare expenditure associated with green space to ensure potential costs (or savings) are not underestimated.

That said, our study is limited by a lack of data on costs associated with mental health ambulatory care hospitalisations and other aspects of healthcare expenditure affected by mental health (e.g. impacts of depression on diabetes treatment adherence[66]). Each of these constitute worthwhile avenues for future investigation to more comprehensively understand how green space may influence healthcare expenditure via mental health. Also, our study is also limited by age group. Data was only available on persons aged 45y or older, which means these results cannot be generalised to younger people, for whom interactions with green space and experiences with negotiating the healthcare system can be quite different. This is an important area for future research.

Our study has further limitations that warrant acknowledgement. While adjustment for income, education and employment status does help to address potential socioeconomic confounding in ways that were not possible in the ecological studies that have dominated thus far, this does not address disparities in wealth that may still influence access to green space and risk of mental ill-health. Although a legion of studies have reported mental health benefits of green space (e.g.[8 67-69]), and that work has been extended by examining different types of green space,[23 39 40] these remain fairly coarse definitions based on data from a single time point. Loss of green space may have occurred in some areas that cannot be taken into account. Meanwhile, changes in green space may also have occurred that influence experiential qualities of a neighbourhood; the look, feel and level of shade in a street lined with jacaranda trees may be quite different from one lined with palms. Similarly, the felt quality and/or state of disrepair may vary between two green spaces of equivalent size in consequential ways for whether people consider them safe places to relax, exercise and meet with neighbours.[70] Research has already shown associations between green space and mental health can be stronger when those green spaces are considered higher quality (e.g.[69 71 72]). How variations in green space quality might influence mental healthcare and associated expenditure remains under-researched, as is the potential intersection with changes in urban form and green space provision that may be closely entwined with wider trends in population growth, densification, local economy, and healthcare provision.

These are common limitations to all studies on green space and mental healthcare thus far and warrant further investigation, especially if the availability of green space not only influences need for mental healthcare, but also effects decisions with respect to how mental healthcare is administered. For instance, it may be that a nearby woodland or botanic garden can be a preferential setting for implementation of some non-pharmaceutical forms of mental healthcare, such as so-called ‘nature prescriptions’ (or ‘green social prescriptions’). Although many nature prescriptions have been implemented, there has been no randomised control trial to test their effectiveness or cost-effectiveness so far.[73] Further work designed to test whether investments in urban greening and health sector-oriented interventions that facilitate greater levels of green space visitation influence mental healthcare expenditure are worth pursuing.

Conclusions

Community greening strategies may well improve mental health among residents and this is a highly laudable goal with a substantial range of co-benefits. But at the same time, this study found individual-level covariate adjusted evidence of increased mental healthcare expenditure associated with urban greening, especially with respect to open grass. A range of complementary avenues for further investigation have been proposed, understanding that this study is among the first to assess association between different types of green space and actual expenditure from multiple forms of mental healthcare, with such analysis key to informing budget constrained healthy place making.

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Table 1: Frequencies and percentages for the three study outcomes by green space availability

	Total N	Antidepressants		Talking therapies		Combined	
		N	%	N	%	N	%
Overall	55,339	11,071	20.01	4,954	8.95	13,482	24.36
Total green space							
0-24.9%	7,172	1,353	18.87	737	10.28	1,752	24.43
25.0-31.9%	9,370	1,732	18.48	836	8.92	2,152	22.97
32.0-39.9%	12,397	2,499	20.16	1,087	8.77	3,013	24.30
40.0-49.9%	14,898	3,194	21.44	1,300	8.73	3,771	25.31
≥50.0%	11,502	2,293	19.94	994	8.64	2,794	24.29
Chi-square (p-value)		38.7	**P≤0.001**	18.2	**P≤0.001**	17.3	**P≤0.001**
Trees canopy							
0-9.9%	5,829	1,394	23.91	525	9.01	1,602	27.48
10.0-19.9%	21,301	4,443	20.86	2,036	9.56	5,403	25.37
20.0-29.9%	14,064	2,722	19.35	1,216	8.65	3,324	23.63
≥30.0%	14,145	2,512	17.76	1,177	8.32	3,153	22.29
Chi-square (p-value)		113.7	**P≤0.001**	18.2	**P≤0.001**	79.4	**P≤0.001**
Grass area							
0-4.9%	6,927	1,183	17.08	658	9.50	1,571	22.68
5.0-9.9%	23,124	4,167	18.02	2,026	8.76	5,226	22.60
10.0-19.9%	14,158	2,925	20.66	1,265	8.93	3,512	24.81
≥20.0%	11,130	2,796	25.12	1,005	9.03	3,173	28.51
Chi-square (p-value)		279.8	**P≤0.001**	3.7	P=0.300	155.0	**P≤0.001**
Age							
45-64 y	26,955	4,907	18.20	3,346	12.41	6,625	24.58
65-74 y	16,515	3,364	20.37	1,145	6.93	3,891	23.56
75-84 y	7,745	1,866	24.09	362	4.67	1,995	25.76
≥85 y	4,124	934	22.65	101	2.45	971	23.55
Chi-square (p-value)		154.9	**P≤0.001**	866.7	**P≤0.001**	16.1	**P≤0.001**
Sex							
Male	25,498	3,845	15.08	1,531	6.00	4,651	18.24
Female	29,841	7,226	24.22	3,423	11.47	8,831	29.59
Chi-square (p-value)		717.0	**P≤0.001**	504.1	**P≤0.001**	961.7	**P≤0.001**
Household income (AUD $)							
0-$29,999	10,396	3,006	28.9	932	9.0	3,320	31.9
$30,000-$69,999	15,956	3,231	20.2	1,388	8.7	3,894	24.4
≥ $70,000	18,490	2,747	14.9	1,777	9.6	3,763	20.4
Missing	10,497	2,087	19.9	857	8.2	2,505	23.9
Chi-square (p-value)		821.6	**P≤0.001**	9.1	**P≤0.001**	483.1	**P≤0.001**
***Educational**							
None	3,389	1,023	30.2	257	7.6	1,101	32.5
School	31,783	6,746	21.2	2,690	8.5	7,993	25.1
University	19,652	3,169	16.1	1,966	10.0	4,240	21.6
Missing	515	133	25.8	41	8.0	148	28.7
Chi-square (p-value)		434.7	**P≤0.001**	43.7	**P≤0.001**	215.1	**P≤0.001**
Work status							
Working	24,953	3,891	15.6	2,666	10.7	5,391	21.6
Retired	25,907	5,770	22.3	1,722	6.6	6,495	25.1
Other	3,738	1,219	32.6	527	14.1	1,388	37.1
Missing	741	191	25.8	39	5.3	208	28.1
Chi-square (p-value)		759.9	**P≤0.001**	380.1	**P≤0.001**	441.4	**P≤0.001**
Relationship status							
Yes	41,331	7,624	18.4	3,254	7.9	9,257	22.4
No	13,444	3,315	24.7	1,641	12.2	4,057	30.2
Missing	564	132	23.4	59	10.5	168	29.8
Chi-square (p-value)		244.9	**P≤0.001**	234.1	**P≤0.001**	333.7	**P≤0.001**

Combined refers to at least one antidepressant prescribed or talking therapy referral without distinction by healthcare type

Figure 1: Multilevel logistic regressions for assessment of associations between 10% increase in green space, tree canopy and open grass, with prescription of antidepressant medications and/or referral for talking therapies, adjusted for potential confounding

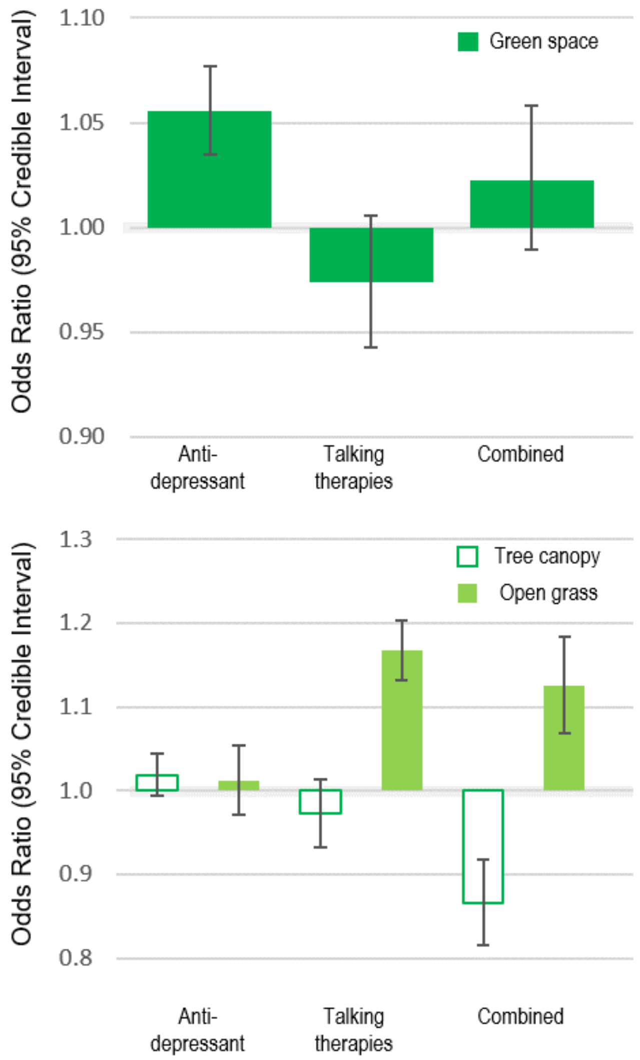


Figure 2: Multilevel negative binomial regressions for assessment of associations between 10% increase in green space, tree canopy and open grass, with counts of prescriptions of antidepressant medications and/or referrals for talking therapies, adjusted for potential confounding and discounting participants with no record of antidepressant prescription or referral for talking therapy

Need more comments to say there are 4 mods, see Table S4

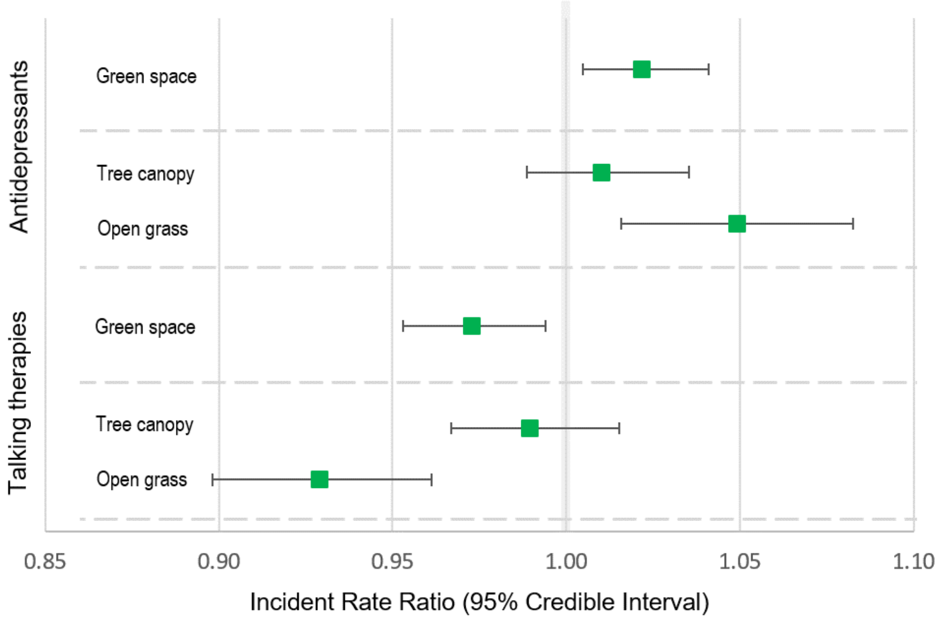
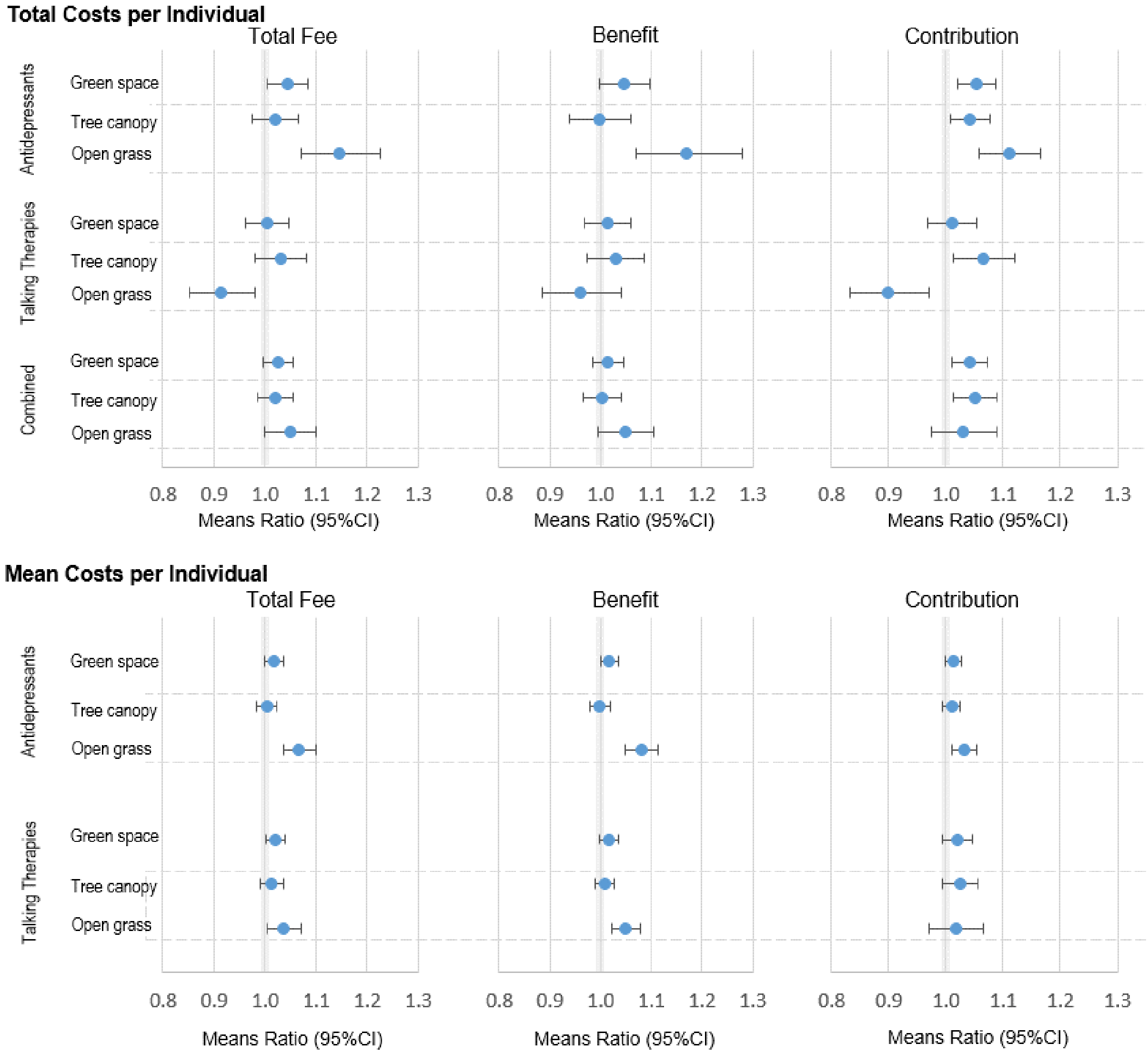


Figure 3: Multilevel generalised linear models with gamma distribution for assessment of associations between 10% increase in green space, tree canopy and open grass, with fees of prescriptions of antidepressant medications and/or referrals for talking therapies, adjusted for potential confounding and discounting participants with no record of antidepressant prescription or referral for talking therapy



Thomas Astell-Burt: Conceptualisation, Methodology, Software, Investigation, Resources, Writing – Original Draft, Writing – Review and Editing, Visualisation, Supervision, Project administration, Funding acquisition

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