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Is Walk Score® associated with Hospital Admissions from Chronic Diseases? Evidence from a Cross Sectional study in a High Socio- Economic Status Australian City State

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Is Walk Score® associated with Hospital Admissions from Chronic Diseases? Evidence from a Cross Sectional study in a High Socio- Economic Status Australian City State

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Abstract

OBJECTIVES: To explore patterns of non-communicable diseases (NCDs) in the Australian Capital Territory (ACT).To ascertain the effect of the neighbourhood built environmental features and especially walkability on health outcomes, specifically for hospital admissions from NCDs.

DESIGN: A cross-sectional analysis of public hospital episode data (2007-2013)

SETTING: Hospitalisations from the ACT, Australia at very small geographic areas.

PARTICIPANTS: Secondary data on 75,290 unique hospital episodes representing 39,851 patients that were admitted to ACT Hospitals from 2007 to 2013. No restrictions on age, sex or ethnicity.

MAIN EXPOSURE MEASURES: Geographic Information System derived or compatible measures of General Practitioner access, neighbourhood Socio Economic Status, alcohol access, exposure to traffic

and WalkScore® walkability.

MAIN OUTCOME MEASURES: Hospitalisations of circulatory diseases, specific endocrine, nutritional and metabolic diseases, respiratory diseases and specific cancers.

RESULTS: Geographic clusters with significant high and low risks of NCDs were found that displayed an overall geographic pattern of high risk in the outlying suburbs of the territory. Significant relationships between neighbourhood walkability as measured by Walk Score® and the likelihood of hospitalisation with a primary diagnosis of Myocardial Infarction (heart attack) were found. A possible relationship was also found with the likelihood of being hospitalised with four major lifestyle related cancers.

CONCLUSIONS: Our research augments the growing literature underscoring the relationships between the built environment and health outcomes. In addition it supports the importance of walkable neighbourhoods, as measured by Walk Score[®], for improved health.

1 2 3 4 5	1	Strengths and limitations of this study
6 7	2	• This is one of the few studies that investigate the relationship between walkability and
8 9	3	hospitalizations from heart disease and specifically myocardial infarction while simultaneously
10 11	4	investigating other chronic conditions and built/social environment drivers of health.
12 13	5	• This is the first study to report a significant relationship between heart attacks and walkability
14 15	6	(measured using Walk Score®).
16 17	7	• While there have been many walkability studies in low SES and demographically mixed areas this
18 19	8	is one of the few to report significant results from a relatively egalitarian, well educated, wealthy
20 21	9	region.
22 23	10	• The cross sectional nature of this study makes it difficult to infer causal relationships.
24 25	11	
26 27	12	
28 29	13	
30 31	14	• The cross sectional nature of this study makes it difficult to infer causal relationships.
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28 Introduction

29 Background

Increasing rates of lifestyle-related non-communicable diseases (NCDs) such as cardiovascular disease and type 2 diabetes remain an area of public health concern in developed (and increasingly in developing) countries. In Australia, NCDs remain the predominant drivers of premature mortality and co-morbidity [1] .The Australian Capital Territory (ACT), is the wealthiestⁱ [2] and best educated state in Australia [3]. It has also been rated as one of the best places in the world to live by the Organisation for Economic Co-operation and Development [4], and has routinely been voted as the most liveable city in Australia [5]. In the annual "Australian Cities Liveability Survey" residents of Canberra have voted the city as being safe, affordable, having good employment and economic opportunities, having plenty of good schools/educational opportunities and an attractive natural environment with a wide range of opportunities for outdoor recreation activities [5]. In addition, there is a relative absence of heavy industry in ACT. Therefore, there is a general opinion that the ACT is an 'exceptional' city state in Australia with regard to its environment and planning. It follows therefore, that such a salubrious environment coupled with an educated population should encourage healthy lifestyle behaviours such as increased physical activity, which in turn should lead to significantly lower rates of lifestyle-related NCDs compared to the rest of Australia. Paradoxically, however, this expectation is not reflected in the ACTs burden of NCDs or lifestyle related risk factors relative to the rest of Australia. For example, adult prevalence of obesity/overweight in the ACT is 62.2% compared to an Australian average of 63.48%[6]. In addition rates of childhood obesity in the ACT are similar to those reported nationally. Furthermore, key environmental indices such as walkability in the ACT are not significantly different from the walkability in other major metropolitan cities in Australia [7]. While city level measures of walkability are of questionable value, our research shows that at the very least there are significant variations in walkability within the ACT, with the majority of suburbs being car dependent.

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Unlike many other cities, a high degree of government ownership and control over land has resulted in a unique pattern of suburb development in the ACT [8]. The planning has attempted to mimic a geographic "central place"[9] hierarchy with each suburb having its own suburb centre with shops, destinations etc. Suburbs are nested within larger districts. The ACT comprises 8 populated districts. Each district has a central suburb, which is usually a very accessible, densely settled geographic central place with access to various local destinations including services, shops and other amenities. Some of these centres are also well served by public transport. Finally, in the centre of the ACT itself is the suburb of 'Civic', the central business district, with a very high degree of destination density. In spite of extensive planning, many suburb centres have over the years, been affected with shop, school and other destination closures [8] resulting in a reduction in the number of local amenities and reduced walkability. Thus, planned and unplanned variations in the cityscape imply that residents are exposed to a variety of physical environments which in turn may result in different health behaviours and resulting NCDs within the geographic boundaries of the ACT. Investigation of the spatial patterns of key NCDs *within* the ACT and their associations with the physical and social environmental features can help identify environments that lead to adverse health outcomes and highlight which design features of these environments are significantly associated with specific health outcomes. In addition to spatial variations in the built environment, an additional aspect that makes the

ACT ideal for studying such relationships is the relatively high Socio Economic Status (SES) of the majority of its residents [2, 3] though there are pockets of poverty [10]. It has been repeatedly demonstrated, that if beneficial relationships do exist between the built environment and healthy behaviours (and consequent health outcomes), they are more likely to be found in high SES locales such

as the ACT [11, 12], since the relationship between environment and behaviour is confounded by a

negative perception of the environment in low SES individuals[13]. Therefore this research project had

two aims: 1) To explore the spatial patterns of NCD-related hospital admissions in a relatively high SES

Australian urban area - the ACT and 2) To investigate the built environmental correlates, adjusted for key

individual level factors.

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84 Methods

Conceptual Framework

We start with a theoretical basis of the well-known public health triad of environment, behaviours and health outcomes. Health outcomes are influenced by health behaviours, which in turn are associated with the environment. We summarize this in Figure 1. In Australia and elsewhere, a number of research papers have established the relationships between environment and behaviours (Link A – see figure 1) [14-16] or behaviours and health outcomes (Link B- see figure 1) [17, 18]. It logically follows that the environment is related to health outcomes through the individual lifestyle behavioural pathway. In addition, the built environment may directly influence health outcomes. For example, air pollution may be detrimental to respiratory and cardiovascular health [19], or perceptions on the environment may affect mental health [20]. However, research on this relationship (Link C-see figure 1) is limited, with most research, excepting a few [21, 22], focussing on outcomes related to sedentary health behaviours such as obesity [23, 24] and conditions directly related to obesity [25]. Our interest, therefore, was in investigating this relationship (Link C- figure 1), between aspects of the physical environment and the four major NCDs in the ACT: circulatory system diseases, specific cancers, Endocrine Nutritional and Metabolic Disorders (ENMDs) and respiratory disorders, using geocoded ACT hospitalisation data (from 2007 to 2013) and specific built environmental attributes.

- 102 Fig 1: Framework of relationships between environment, behaviours and health outcomes
- 103 -----

105 Investigating Relationships

106 To investigate relationships between the built environment and NCD-related hospital admissions, we

107 followed a combined exploratory-inferential approach. First, we asked "What are the spatial patterns of

108 the four key chronic conditions in the ACT?" This is addressed through exploratory mapping using

109 spatial cluster analysis. Second, we investigated relationships between various individual and

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environmental predictors such as neighbourhood walkability, traffic volume, and access to off-license

alcohol outlets and the key NCD-related hospital admissions in the ACT. In the next section, we explain

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112 in detail the methods used to achieve this. The research was approved by the ACT Health Human 113 Research Ethics Committee (Ref.: ETH.11.14.310) on 8th December, 2014. 114 Data 115 116 **Hospital Data** 117 118 ACT Admitted Patients Data Collection (APDC) data were supplied by the ACT Health Directorate. This 119 consisted of 75,290 unique hospital episodes representing 39,851 patients admitted to all ACT public 120 hospitals between 1st January 2007 and 31st December 2013. Data were provided after ethics and other 121 data regulation requirements from the data custodian at HealthInfo@act.gov.au had been met. Public 122 hospitals capture around 80% of all hospitalisationsⁱⁱ in Australia [26]. The patient hospital admission 123 data had Australian Census – Australian Bureau of Statistics (ABS) Mesh Block (30 to 60 dwellings), 124 Statistical Areas Level 1 (SA1s) (200-800 people) and SA2 (3,000-25,000 people) geocodes attached to 125 them, therefore no additional geocoding was necessary. Geocoding completeness [27] varied with 126 geographical scale with 7,284 records missing at Mesh Block level, but only 949 missing at the SA2 level. 127 A single hospital episode included a primary diagnosis and up to a hundred other diagnoses. 128 129 Selection of NCDs 130 131 While all hospitalisations for four ICD-10 codes: E, C, J and I, were provided, we divided the data into 132 specific sub-codes, removing conditions with obvious genetic or familial drivers (i.e. not directly related to 133 lifestyle risk). Note that these ICD-10 codes could have been a primary or an additional diagnosis. Each 134 condition was analysed separately and with comorbidity. The subsets of ICD-10 codes used in our 135 analyses were:

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A) Circulatory Diseases: all diseases of the circulatory system i.e. ICD 10 (I00-I99) code 'I' (circulatory

137 system diseases or CSDs). However, we also created a data subset of hospital admissions with a primary

- diagnosis for Myocardial Infarction (MI) and subsequent infarctions (ICD 10 codes I21 and I22
- 139 respectively). MI or heart attack represents a serious and sudden event generally requiring immediate
- 140 hospitalisation.
- 141 B) Cancers: We included cancers of the breast 'C50', colorectal cancers 'C18-C21', Endometrial Cancer

142 'C54.1' and lung cancers 'C33-C34'. These cancers have been associated with lifestyle risk factors [28].

143 C) Endocrine, Nutritional and Metabolic Diseases (ENMDs) - E10-E16 and E-66.

144 D) **Diseases of the Respiratory system** – J00-J99 i.e. all diseases of the respiratory system.

145 Table 1 describes the overall episodes of hospitalisation related to NCDs.

Table 1: Total hospitalisations for each non-communicable disease category by year^a

Specific	Respiratory	CSD	MI	ENMD	Any of the four
cancers	system				major NCDs
573	3381	4992	369	1673	8051
661	3762	5314	415	1618	8796
709	3639	5492	528	1411	8913
680	3646	5126	516	1075	8563
716	4203	5379	530	793⁺	9316
714	4405	5458	543	1498	9453
704	4273	5391	491	2041	9234
	cancers 573 661 709 680 716 714	cancerssystem573338166137627093639680364671642037144405	cancerssystem573338149926613762531470936395492680364651267164203537971444055458	cancerssystem573338149923696613762531441570936395492528680364651265167164203537953071444055458543	cancerssystem57333814992369167366137625314415161870936395492528141168036465126516107571642035379530793*714440554585431498

^a Some hospitalisations were for multiple conditions, thus totals with any of the four major NCDs were less than the sum of
 single NCDs; CSD-circulatory system disease, MI–myocardial infarction; ENMD–endocrine, nutritional and metabolic diseases;
 NCD–non-communicable disease; + The numbers of ENMDs in 2011 are anomalously low, the reason for this is not known.

151 Of these conditions CSDs and ENMDs are known to be associated with a sedentary lifestyle, as is

152 obesity, colorectal and endometrial cancer [28]. Lung cancers and respiratory diseases are driven to a great

153 extent by smoking and air quality.

155 For statistical modelling and analysis, we used all hospital admission episodes (2007-2013), but for spatial

156 mapping we further sub-divided the hospital data to the years 2007 and 2011 because these link to the

157 national censuses (2006 and 2011) with available reference population data. A number of individual level

158 covariates were included in the hospital data: gender, age (years), marital status, private insurance and

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159	hospital insurance. The last two variables may serve as proxy measures of SES. The covariates are
160	summarized in Appendix S1 Table S1.1.
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162	
163	Population Data
164	
165	In addition to the above data, population data were required for mapping rates of hospital admission. The
166	smallest geography at which Australian demographic data (for example age, gender, SES) are released is
167	the Statistical Area 1 (with an average of 500 people). SA1 is therefore a relatively small geographic area at
168	which NCD-related hospital admission rates could be mapped. However, there were relatively smaller
169	numbers of neoplasm and MI cases (Table 1) hence these conditions required a larger geography, - the
170	SA2 (suburb) for mapping because rates based on small numbers of expected cases are unstable and have
171	large confidence intervals. Therefore we aggregated up to the Statistical Area 2 (SA2 - suburb) level. In
172	addition, while ENMDs and CSDs can be mapped at SA1s annually given their large annual numbers in
173	the ACT (Table 1), aggregate sums over multiple years were used for MI and neoplasms.
174	
175	Australian census output geographies changed significantly between 2006 and 2011. While, there are
176	minimal differences between 2011 SA2 geographies and their 2006 counterpart Statistical Local Areas
177	(SLAs) in the ACT [29], there was significant spatial mismatch between 2011 SA1s and their 2006
178	counterpart in the census hierarchy- Collection Districts(CDs). Thus, when mapping by SA1s or CDs
179	(ENMDs, respiratory diseases and CSDs), we show separate maps for 2006 and 2011. Age specific 2011
180	population counts at SA1s and 2006 counts at CDs were obtained from the ABS. For SA2 level maps of
181	neoplasms and MI, counts of expected numbers of cases for the years 2007-2011 were required. Age
182	specific 2011 population counts and 2006 population counts were obtained at SA2s/SLAs. To obtain the
183	age distribution for the intermediate years (2007-2011) at SA2s, we linearly interpolated the numbers in
184	each SA2/age group between 2006-2011. This generated the fraction of people in each age group in a
185	given year in a SA2. We then used an indirect age standardization technique to calculate annual expected
186	numbers of cases of an NCD using the annual age distributed ACT population as the standard population

407	
187	[30]. Expected annual numbers were also calculated for the CD, SA1 and SA2 data. We used 2006
188	expected counts when mapping 2007 hospitalisation data since 2007 SA1 or CD population counts were
189	not available.
190	
191	
192	Environmental Data
193	As summarised in Figure 1, we wanted to investigate relationships between various built environmental
194	attributes and health events ((hospital admissions). A number of environmental covariates were collected,
195	collated and/or created in-house by the authors. Our choices of environmental drivers were informed by
196	previous research but also constrained by the available data. For example, we did not have geocoded data
197	for food outlets so could not explore any relationships between hospital admissions and the food
198	environment. The environmental indices that were available are described below:
199	1. Walkability: Walking is the most prevalent form of physical activity in the population [31,
200	32]. The degree of neighbourhood walkability predicts the degree of walking[33]. We
201	measured the physical activity environment through suburb level walkability. While other
202	aspects of the physical activity environment such as access to parks and leisure/exercise
203	centres are also important, the walking network remains one of the most important built
204	environmental attributes for overall physical activity [34]. Walk Score® is a measure of
205	walkability produced by a United States based company that has been validated [33] and has
206	been utilized in a number of public health studies in the United States. In the Australian
207	context, it has been found to have strong relationships with walking for transport in a recent
208	study [14], though relationships with health outcomes have not previously been found [21].
209	Walk Score [®] is a composite measure of destination density. The scores are normalized to a 0
210	to 100 scale, with 0 being the lowest walkability and 100 being the highest. A five scale
211	categorization is used; "Walkers Paradise" (Walk Score® 90-100), "Very Walkable" (70-89),
212	"Somewhat walkable" (50 to 69), "Car-dependent" (25 to 49)" and "Car Dependent" (0-24)
213	by the developers of Walk Score® [35] and these categories have been used by other

1 2		
3	214	researchers [16]. Walk Scores® for ACT suburbs/SA2s were obtained from the Walk
4 5	215	Score® website [35]. A map of Walk Scores® at ACT suburbs is provided in Figure 2.
6 7	216	
8 9	217	Fig 2: Map of five categories of Walk Score® by ACT suburbs
10 11 12	218 219	The five categories are "Walkers Paradise" (Walk Score® 90-100), "Very Walkable" (70-89), "Somewhat walkable" (50 to 69), "Car-dependent" (25 to 49)" and "Car Dependent" (0-24)
13 14	220	
15 16	221	
17 18	222	2. Access to General Practitioners: access to primary care is an important predictor of
19 20	223	admittance into tertiary facilities [36, 37]. Access to General Practitioners (GPs) is related to
21 22	224	better health management and lesser use of hospital services [36, 38]. We created an access
23 24	225	measure by drawing a circular buffer around the Mesh Blocks of the patients in the
25 26	226	hospitalisation data. The circular buffers around the Mesh Blocks adaptively grew to
27 28	227	different sizes, with each buffer growing until a total of 1000 people were included in the
29 30	228	circle. The numbers of GP clinics in the buffer circles were then summed to provide an
31 32	229	approximate measure of access as the number of GP clinics per thousand persons. GP clinic
33 34	230	data for 2010 were provided by the ACT Medicare Local, while underlying 2011 census
35 36	231	population data were obtained from the ABS.
37 38	232	
39 40	233	
41 42	234	3. Neighbourhood SES: is a well-established marker of social environment including crime and
43 44	235	social cohesion and a mature literature supports the relationship between neighbourhood
45 46	236	SES and a range of health outcomes [39]. The Socio-Economic Indexes for Areas (SEIFA)
47 48	237	are indices of area level of Socio-Economic Status in Australia developed by the ABS. The
49 50	238	Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD) is one such index
51 52	239	that measures both advantage and disadvantage. The index was created by incorporating a
53 54	240	number of measures including percent unemployed, car ownership and percent disabled.
55 56	241	SA1 level IRSAD scores, the finest resolution at which they are available were incorporated
57 58	242	into these analyses.
59 60		9

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244	4.	Alcohol outlets: along with the food environment alcohol outlets are powerful predictors of
245		lifestyle-related health outcomes [40]. While the food environment is best represented by
246		summary measures of access to a range of food outlets, we did not have access to an
247		integrated, clean, geocoded dataset of food outlet locations in the ACT for this study (see
248		Discussion). Easy access to alcohol has been related to a number of negative health and
249		social outcomes [41, 42], and we have used a measure of alcohol access in our analyses. A list
250		of all licensed off-license liquor outlets was obtained from the ACT Department of
251		Regulatory Services and geocoded to SA1 level. Off-license outlets are licensed to sell
252		alcohol, but alcohol cannot be consumed within premises, examples of which include
253		supermarkets and bottle shops. The mean distance to off-license liquor outlets from each
254		patient SA1 served as a measure of access to alcohol.
255		
256	5.	Road Traffic Exposure: The presence of road traffic can act as an impediment to physical
257		activity in a neighbourhood environment [43]. We thus created a measure of exposure to
258		road traffic using methods published earlier [43].
259		

260 Analysis

261 Spatial patterning of hospital admissions related to NCDs were explored using a cluster detection tool,

the Spatial Scan Statistic [44]. Monte Carlo regression was then employed to investigate relationships

263 between environmental attributes and hospital admissions [27, 45]. Finally, a negative binominal was also

264 employed to test the relationship between NCDs and built environmental factors.

265

266 Exploratory Spatial Scan Statistic

267 Exploratory methods allow us to generate hypotheses about relationships (Link C, Figure 1) by visually

- 268 correlating significant spatial patterns of NCD-related hospital admissions with spatial patterns of
- 269 environmental variables. We used the well validated and robust Spatial Scan Statistic to investigate

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270	significant spatial patterns [44, 46, 47]. This method asks "What area or what combination of areas is most
271	likely to have a statistically significantly 'high' or a significantly 'low' risk relative to areas outside the
272	combination of areas?" This would be framed as a "cluster detection problem" in the spatial
273	epidemiology literature [44].
274	
275	The Spatial Scan Statistic was implemented using the SaTScan software. This method implements a single
276	maximum likelihood based hypothesis test over geographic space to identify the regions where the
277	distribution of cases relative to controls/population (or the expected number of cases) is most likely to be
278	consistent with a significant excess risk. To implement this, SaTScan identified candidate clusters, which
279	were circles of increasing radii, bound by a maximum population threshold radius (set here to 5% of the
280	population), centred on pre-specified locations such as SA1 centroids. The size of the cluster is
281	sometimes sensitive to the threshold radius [48]. The 5% threshold represents around a few hundred
282	expected cases of most NCDs, and is sensitive enough to delineate small clusters, an early goal in our data
283	exploration and analysis.
284	Over many candidate clusters SaTScan maximizes the likelihood ratio, given by
285	LLR=O*ln(O/E)+O*ln((n-O)/(n-E))
286	Where, LLR represents the logarithm of the likelihood ratio, O are observed cases, E are expected cases,
287	and n is the total number of cases in the entire region (ACT). The likelihood formula assumes that NCD
288	cases are distributed as a Poisson random variable and the likelihood ratio is compared to simulated
289	likelihood ratios generated from 999 Monte Carlo randomizations of the data to assess statistical
290	significance. The area that has the highest likelihood value (or the lowest p value) is the primary cluster. If
291	both low and high risk clusters are searched for then the most likely (high and low) clusters will be
292	identified and published by the software. Secondary or less likely clusters may also be reported. In our
293	analyses we restricted our results to primary or secondary clusters with a significant p value. Relative risks
294	at the significant clusters were reported as: (risk inside the cluster)/(risk outside the cluster.)
295	SaTScan analyses were implemented for CSDs and respiratory diseases at the SA1 scale for 2011 and CD
296	scale for 2007. Because of an unexplained anomalously low number of hospitalisations for ENMDs in
	11

2011 (Table 1), we scanned 2012 SA1 and 2007 CD ENMD data. Due to lower event rates, MI and
selected cancers were analysed at the SA2 scale for the entire aggregated 2007-2011 period. Thus, SA2
level observed and expected numbers were summed for the entire 5 year period 2007-2011. Results were
mapped using ArcGIS 10.1.

302 Associations between built environment factors and hospital admission

- 303 rates

events and built environment characteristics. The hospital admission data were complex, with multiple
cross classifications and nesting. For example, each person in the data could be hospitalised multiple
times (nesting of hospitalisation episodes within people), people were nested in geographic
neighbourhoods such as suburbs, and the temporal nature of the data, implies likely temporal trends and
seasonal patterns. In addition, the distributions of a number of predictors such as suburb level Walk
Score® or GP density were not normal, which would render traditional linear models unusable, or require

We used two different models to investigate the relationships between the various NCD-related hospital

312 complex statistical transformations and/or models. To overcome this problem we first modelled

313 relationships using a robust method: Monte Carlo logistic regression [27, 45]. The approach was as

314 follows:

1. Randomly sample 50% of the data

316 2. Fit logistic regressions (or any other model to be tested) to estimate best explanatory model, store

- 317 parameter estimates: intercept and slope values
- 3. Repeat steps 1 and 2, N times (In our simulations N=1000)

319 4. Calculate mean and 95% confidence intervals for estimated model parameters from stored values in320 step 2.

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We utilized logistic regressions as our explanatory model, with respiratory diseases as the control condition. Respiratory disorders were chosen as the control condition because the drivers of respiratory disorders, with the exception of smoking, generally differ from the environmental drivers of the other three conditions. (While ideally we would have liked to use all hospitalisations as controls, these data were not available at the time of analysis). Separate models were run for each of MI, CSDs, specific neoplasms and ENMDs. When modelling neoplasms, since lung cancers have somewhat different environmental drivers than the remaining cancers, we ran the model with and without lung cancer. We also attempted to model hospitalisations with comorbid CSDs, specific neoplasms, ENMDs and respiratory diseases conditions by coding hospitalisation with more than one condition as 1, and the rest 0.

Finally, for NCDs with significant environmental correlates in the Monte Carlo model we also modelled the total number of hospitalisation events of a given condition in a given suburb as a function of counts of different predictors. The models can be written as:

 $Y_j \sim Negbin(\mu_j, \kappa)$

 $\mu_{j} = e^{(\beta 0 + \sum_{k} \beta_{k} x_{jk})}$

Where Y_i is the total count of a given condition in suburb j and x_{ik} is the count of the k'th predictor in the j'th suburb, for example, - the total number of insured patient hospitalisations in a suburb or total number of female patient hospitalisations in a suburb. Yi was considered to be negative binomially distributed with mean μ_i and variance κ . A negative binomial model was used after it was found that the data were overdispersed, rendering a Poisson model unsuitable. The mean μ_i or suburb level count of a given outcome was modelled as an exponential function of an intercept term β_0 and a slopes term β_k . These models require aggregate counts or summaries at the suburb level, and variables were recoded to satisfy this requirement. Thus, for example, discrete variables such as the marital status of a hospitalised person (1/0) translated to the total number of hospitalisations of married people in a given suburb. Continuous variables were similarly recoded, such as the number of hospitalisations of people in the topmost quartile of traffic exposure, number of hospitalisations of people in lowest decile of IRSAD,

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number of hospitalisations of people with good GP Access and so on. People with a GP density of 1 or

more in their immediate buffer neighbourhood were considered to have good access.

The models were implemented using R and Stata.

Results

Figures 3 to 6 display the results of the Spatial Scan Statistic analyses. We report all significant clusters of both 'high' and 'low' risk. Reporting all significant clusters instead of the "most likely" cluster has been shown to enhance exploratory analyses [48, 49]. The scan results displayed a general trend of higher risk of hospital admissions in the outer suburbs and lower risk in the inner suburbs. Thus, the suburbs of Civic and Kingston-Barton either had significantly lower risk of CSDs (Figure 3), MI (Figure 6) and respiratory diseases (Figure 5) or were not significantly different clusters (Figures 3-6). While maps of all CSDs showed some random variation from 2007 to 2011, sections of West Belconnen around Fraser and areas south of Gowrie; and north of Gunghalin showed consistent high risk of CSDs (Figure 3). Some of these areas also showed consistent high risks of ENM diseases (Figure 4). Fig 3: Spatial patterns of CSD risk Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with statistically significantly different risks of hospitalisation for all CSDs. Expected counts for 2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT. Fig 4: Spatial patterns of ENMD risk Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2012* with statistically significantly different risks of hospitalisation for selected ENMDs. Expected counts for 2007 were calculated using 2006 census populations and census 2011 for 2012. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT. * see text for clarification

Fig 5: Spatial patterns of respiratory disease risk

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374 375 376 377	statistically significantly different risks of hospitalisation for respiratory diseases. Expected counts for 2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was
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380	
381	The spatial patterns of MI and cancer risk (Figure 5) did not show a consistent pattern though we can see
382	that the suburbs that are a 'Walker's Paradise' such as Civic, Kingston-Barton and Belconnen were either
383	low risk (Relative Risk/RR <0.13) clusters or were non-significant clusters. One of the recognized
384	problems with SaTScan is its propensity at larger geographic scales to detect large low risk clusters in
385	rural, sparsely populated areas. Thus, areas North East of Gungahlin, and some areas south east of
386	Kingston-Barton appear as low risk clusters, which in reality have very few residents (Figure 6).
387	
388 389 390	Fig 6: Spatial patterns of MI and cancer risk
390	
390 391 392 393	Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to
391 392	Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT.
391 392 393	Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT.
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391 392 393 394 395	Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT.
391 392 393 394 395 396	 Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT. The results of Monte Carlo logistic regressions showed significant relationships between suburb level Walk Score® and the risk of Myocardial Infarction (Table 2). Specifically there was a 4% 1.04 (95% CI:
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391 392 393 394 395 396 397 398 399 400 401	 Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT. The results of Monte Carlo logistic regressions showed significant relationships between suburb level Walk Score® and the risk of Myocardial Infarction (Table 2). Specifically there was a 4% 1.04 (95% CI: 1.01, 1.07) increased odds of being hospitalised for a heart attack from living in a neighbourhood that is not a "Walker's Paradise". Similarly, there was a significant progressively increasing risk of being hospitalised with cancer when living in increasingly less walkable suburbs. When lung cancers were removed from the set of four cancers (not shown), the effect sizes remained the same, but the confidence intervals widened, becoming marginally non-significant. This probably indicates that the relationship with
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Table 2: Summary of robust Monte Carlo logistic regression model fit coefficients (CI) for each NCD hospitalisation outcome*

Predictor	CSD	МІ	ENMD	Selected Neoplasms	More than one comorbic NCD
Individual Level Variables					
(Intercept)	1.09 (0.98 , 1.21)	0.99 (0.95 , 1.02)	1.14 (1.02 , 1.27)	0.85 (0.81 , 0.9)	0.02 (0, 0.13)
Female	0.95 (0.94 , 0.96)	0.97 (0.97 , 0.98)	0.95 (0.94 , 0.96)	1.09 (1.08 , 1.10)	0.86 (0.83 , 0.90)
Age in years	1.01 (1.01 , 1.01)	1(1,1)	1(1,1)	1(1,1)	1.04 (1.04 , 1.04)
Married	1.11 (1.1 , 1.12)	1.02 (1.01 , 1.02)	1.04 (1.03 , 1.05)	1.06 (1.05 , 1.07)	0.93 (0.89 , 0.98)
Paid with private insurance	0.99 (0.98 , 1.01)	1.06 (1.05 , 1.07)	0.99 (0.97 , 1.01)	1.08 (1.07 , 1.10)	0.98 (0.91 , 1.06)
Has hospital insurance	1.02 (1.01 , 1.03)	0.98 (0.97 , 0.99)	0.99 (0.98 , 1.01)	0.97 (0.96 , 0.98)	0.90 (0.84 , 0.95)
Ecological Variables					
Access to GP clinic	1(1,1.01)	1(1,1)	1(1,1)	1(1,1)	0.99 (0.97 , 1.01)
Walk Score [®]					
Reference: Walker's paradise (Score 90 to 100)	х				
Very walkable (Score 70 to 89) or Somewhat walkable (Score 50 to 69)	1.02 (0.92 , 1.13)	1.04 (1.01 , 1.07)	1.07 (0.97 , 1.19)	1.06 (1.01 , 1.12)	1.87 (0.37 , 9.4)
Car-dependent (Score 25 to 49) or Car dependent (Score 0 to 24)	1.03 (0.93 , 1.14)	1.04 (1.01 , 1.07)	1.09 (0.98 , 1.2)	1.07 (1.01 , 1.12)	2.02 (0.04 , 10.24)
IRSAD score	1(1,1)	1(1,1)	1(1,1)	1(1,1)	1(1,1)
Mean distance to off-license alcohol outlet Log traffic exposure	1(0.99,1.01) 1(1,1)	1 (0.99 , 1.01) 1 (1 , 1)	1 (0.99 , 1.01) 1 (1 , 1)	1 (0.99 , 1.01) 1 (1 , 1)	0.92(0.88,0.96) 1(1,1)
Pseudo R ^{2 a}	16.83	95.5	3.54	22.3	10.16

* Significant effects in bold. Significance levels were not computed for Monte Carlo estimates; X Walker's Paradise is the reference category while the two car dependent and two walkable categories are aggregated,^a Pseudo R² is a measure of the amount of variation explained by the model; CI-95% confidence interval; NCD-non-communicable diseases; CSD-circulatory system diseases; MI- myocardial infarction; ENMD-endocrine, nutritional and metabolic diseases; GP-General Practice, IRSAD-Index of Relative Socioeconomic Advantage and Disadvantage

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The relationships were supported by the negative binomial model (Table 3). Somewhat counter-intuitive, relationships with hospital admissions from neoplasms were found, where those living in a poorer neighborhood or having less access to GPs decreased the likelihood of a hospitalisation which may suggest the potential for missed diagnoses. Being female was protective for circulatory disease, myocardial infarction, ENMD or hospitalisation with more than one condition but was a risk factor for selected neoplasms (Tables 2, 3). Being married (or in a de-facto relationship) increased the risk of being hospitalised with any condition but decreased the risk of being hospitalised with multiple conditions (Tables 2, 3). In Australia, while public hospital services are free, patients may have the choice of accessing private services for a fee, usually paid through insurance. Paying with private insurance was positively associated with MI hospitalisation or hospitalisation with selected neoplasms. Since people with cancer often buy private insurance to obtain services not easily accessible in the public system, the association with neoplasm was expected. Similarly, MI patients may choose immediate, higher quality care which the private system may be better positioned to provide. Overall, the results of the regressions agreed with results of exploratory mapping - that is, the outlying low walkability suburbs have higher rates of key NCD-related hospital admission.

Table 3: Summary of negative binomial model fit coefficients (CI)^a

Number of hospitalisations of :	MI Selected Neoplasms	
Females	0.0005 (-0.0022 , 0.0032)	0.0007 (-0.0036 , 0.005)
Married people	0.0032 (0.0016 , 0.0049)**	0.0036 (0.0004 , 0.0068) +
Paid with private health insurance	0.0032 (-0.0024 , 0.0087)	0.0047 (-0.0047 , 0.014)
People with with hospital insurance	-0.0042 (-0.0076 , -0.0008)*	-0.0048 (-0.011 , 0.0014)
People within 1 km distance to off-license alcohol outlets	-0.0001 (-0.0005 , 0.0003)	0.0001 (-0.0008 , 0.0009)
People 44 and younger	-0.002 (-0.0073 , 0.0033)	-0.0172 (-0.0314 , -0.0029) +
People 45 to 64	-0.002 (-0.0077 , 0.0038)	-0.0116 (-0.0266 , 0.0034)
People 65 and over	-0.0003 (-0.0057 , 0.005)	-0.0145 (-0.0289 , -0.0001)
People with good GP Access	0.002 (-0.0037 , 0.0077)	0.0171 (0.0033 , 0.0308)*
People living in suburbs that are a "Walker's Paradise"	-0.0466 (-0.0871 , -0.022)*	-0.1 (-0.2302 , -0.0426)*
People in "Very Walkable" or "Somewhat Walkable" suburbs	-0.0001 (-0.0003 , 0.0002)	0.0002 (-0.0003 , 0.0008)
People in lowest decile of IRSAD	0 (-0.0006 , 0.0007)	-0.0019 (-0.0035 , -0.0004)*
People in topmost quartile of traffic exposure	-0.0001 (-0.0005 , 0.0003)	-0.0005 (-0.0014 , 0.0004)

^a Significant effects in bold - Key: p<0.001 **, p<0.05 *, p=0.05⁺

CI-95% confidence interval; MI-myocardial infarction; GP-General Practice ;IRSAD-Index of Relative Socioeconomic Advantage and Disadvantage

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422 Discussion

423	We found that Walk Score® was significantly associated with hospital admission for MI. The spatial
424	patterns of MI admission rates and Walk Score® supported this finding. Thus, individuals residing in a
425	neighbourhood considered a "Walker's Paradise" (e.g. Civic) have significantly lower risks of admission
426	for MI after adjustment for age, gender, marital status and insurance status. A similar relationship existed
427	with certain neoplasms though further investigation is required to support this finding. The highest risks
428	of neoplasms and MI admission rates were found in Kambah (Walk Score®: 28) and Kaleen (Walk
429	Score®: 39) which were classified as 'Car Dependent' by Walk Score®. While a number of studies have
430	shown that Walk Score® is related to walking for recreation and transportation [14-16, 33] ours is one of
431	the few studies [21, 22] that showed a significant relationship between Walk Score® and hospital
432	admissions.
422	
433	Our analyses utilized suburb level Walk Scores [®] . It is known that there are significant differences in
434	walkability within suburbs, and therefore individual residential level Walk Scores® could capture more of
435	the variation in walkability in the ACT, and perhaps help in obtaining more robust estimates of the
436	relationships between key NCD-related hospital admission and walkability. Walk Score® itself, has been
437	criticized by some researchers as a measure of walkability though some of these criticisms, - such as the
438	use of "as the crow flies" distance have been rectified in the newer versions of Walk Score®, which we
439	have used [35]. Another shortcoming with the Walk Score® and other environmental data used in these
440	analyses is that they are from a single time point over the analysis period. While theoretically temporal
441	synchronisation between the environmental data and the health data is ideal, accessing archived spatial
442	datasets for different time periods of interest was not possible in a reasonable timeframe for this study.
443	Our data are from public hospital data, and we did not have access to private hospital data. While there is
444	a possibility that this may cause biases, public hospitalisations cover the majority of hospitalisations in the
445	ACT, and therefore are mostly representative of hospitalisations in this population [26]. Nevertheless, it is
446	possible that there are suburb level (or smaller area) variations in the proportion of private hospital

447 admissions relative to public hospital admissions. This may cause biases the extent of which are not

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known. Some of the areas with consistent low risk, such as Civic and Kingston-Barton (at the centre of the ACT) are areas with high residential density, easy access to shops and public transport. These areas also tend to draw a higher proportion of individuals who are younger and mobile, and are less likely to be hospitalised for any condition whatsoever. Since our regression models do not incorporate underlying population data, it is possible that variations in area level populations may affect our analyses. Nevertheless, exploratory cluster mapping *does* incorporate underlying population and we note that areas such as Civic, Phillip, Kingston-Barton were generally low risk clusters. Therefore the relationships are unlikely to be biased by population heterogeneity in hospitalisation rates. A recent similar study from Australia found no significant association between Walk Score® and the likelihood of Ischemic Heart Disease [21]. There could be multiple reasons for this, including the fact that the Walk Score[®] at geographic centroids of SLAs were used to summarize the Walk Score[®] in a given SLA. Since there is considerable variation of Walk Score[®] within an SLA, a geography much larger in size than SA2s in the aforesaid study, using centroid Walk Scores® may not be appropriate. In contrast we used an SA2/Suburb level Walk Score[®], which represents the average Walk Score[®] at the suburb level. Another reason as to why significant associations were not found in the study [21] could be the outcome investigated, - Ischaemic Heart Disease (IHD). This condition, like CSD, may remain undiagnosed in the population resulting in a hospitalisation dataset that is not representative of the true patterns of the condition in the population. MI, which is a severe acute outcome of undiagnosed IHD or CSD, is less likely to suffer from diagnostic bias. To our knowledge, at least one other study, in this case reporting results from the United States, has reported an association between mixed land use, better access to fitness facilities and a lower risk of coronary heart disease in low income women [22]. The local government area of ACT is high SES and relatively egalitarian being at the middle of the income inequality league relative to other local governments in Australia [50]. Car ownership in the ACT (603 per 1000 people) is well above the Australian average (568 per thousand) with only two states, Victoria and South Australia having higher ownership rates. In addition, public and active transport modes of travel to work are less popular in the ACT compared to other capital cities [51]. The combination of high SES, low walkability and high car ownership is known to discourage walking (recreational or transportation walking) [11, 12], which in turn may influence the risk of heart disease or cancer, as demonstrated in this

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476 study. It is possible that cars may enable informed individuals to shop for healthy foods, but the food
477 environment beyond alcohol is not explored in this study. Incorporating the food environment in our
478 analyses is an area of future work.

Another limitation of our study is that we used respiratory disorders as our control condition in the regressions. This is because the drivers of respiratory conditions are generally different from the drivers of heart attacks, ENMDs etc. While our data, which were limited to the four conditions, constrained the analyses to this specific control, future analyses will attempt to incorporate all hospitalisations as control condition. We showed that there are relationships between walkability as measured by Walk Score and key NCDs providing support of the logical link between environment, behaviours and health outcomes (Figure 1: Link C). Nevertheless, we remain interested in investigating Link A, the relationship between environment and behaviours. Since 2013 data on life-style risk behaviours at the suburb level such as smoking/alcohol and BMI have become available through the ACT Adult health survey. Incorporation of these data into further analyses remains an area of future exploration. Furthermore, if individual level address information of the survey respondents were available, this would allow a more precise and accurate investigation of the effects of the built environment on lifestyle risk behaviours and NCDs.

Conclusion

492 Our analyses form a unique and systematic investigation into the effect of built environment and 493 consequent NCD-related hospital admissions. This research highlights the significant role that walkability, 494 plays in health and in use of health care resources i.e. hospitals. While this research could have significant 495 bearings on local policymaking, it also captures a niche in the broader built environment and health 496 literature with its investigation of relationships between the built environment and health outcomes.

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511	Appendix S1: Summary of key individual level covariates in hospitalisation data
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517	
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519 520	None declared
521	
522	Contributions
523 524 525	SM, VL and TC implemented the data cleaning, statistical analyses and the writing. RD, HP and BC provided analytical oversight, reviewed the manuscript and helped with the writing.
526	
527	Data Sharing Statement
528 529 530 531	The hospital data were provided after ethics and other data regulation requirements from the data custodian at <u>HealthInfo@act.gov.au</u> . Anyone with the appropriate ethics clearances can request the data custodian for the data.
532 533	Ethics statement and

1		
2 3 4	534	The research was approved by the ACT Health Human Research Ethics Committee (Ref.:
4 5 6	535	ETH.11.14.310) on 8th December, 2014.
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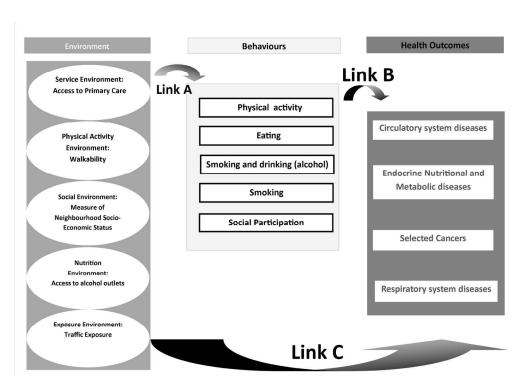
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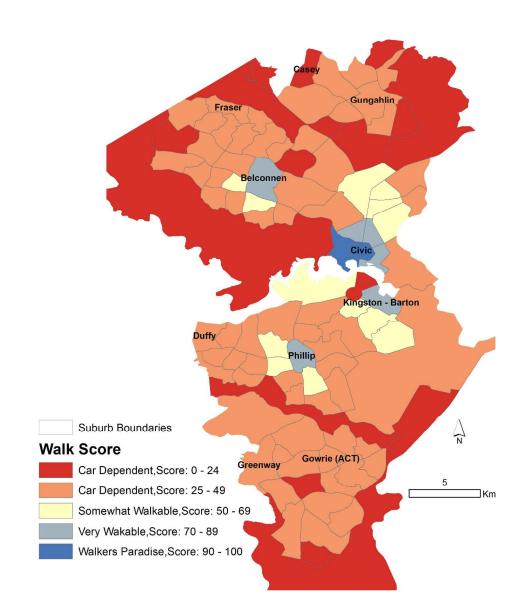
¹ Median Household income/week in 2011-12 was AUD 2,124 compared to a national average of AUD 1,612

ⁱⁱ This is a national statistic. The ACT government does not collect and/or publish private hospitalisation data, but it is unlikely to differ significantly, since states that do publish data report similar fractions of public and private hospitalisations.



Framework of relationships between environment, behaviours and health outcomes (Link C- figure 1), between a 155x110mm (300 x 300 DPI)

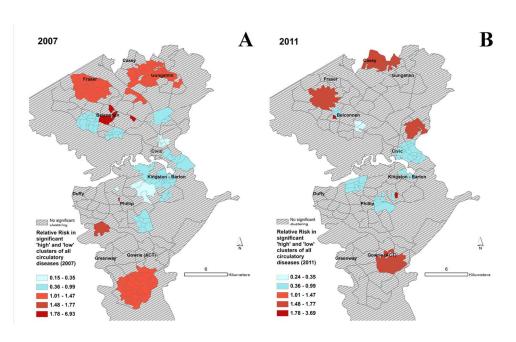
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Map of five categories of Walk Score® by ACT suburbs. The five categories are "Walkers Paradise" (Walk Score® 90-100), "Very Walkable" (70-89), "Somewhat walkable" (50 to 69), "Car-dependent" (25 to 49)" and "Car Dependent" (0-24) "Somewhat walkable" (50 to

186x241mm (300 x 300 DPI)





Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with statistically significantly different risks of hospitalisation for all CSDs. Expected counts for 2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT.

While maps of all CSDs showed 131x79mm (300 x 300 DPI)

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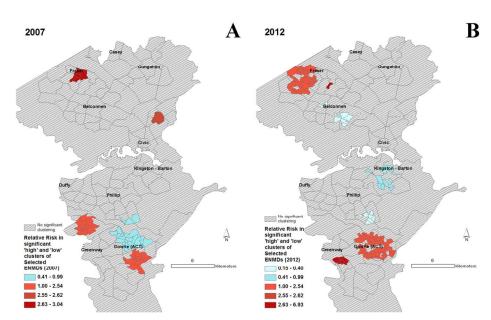


Fig 4: Spatial patterns of ENMD risk

Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2012* with statistically significantly different risks of hospitalisation for selected ENMDs. Expected counts for 2007 were calculated using 2006 census populations and census 2011 for 2012. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT. * see text for clarification

While maps of all CSDs showed 131x79mm (300 x 300 DPI)

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al Area 1s in 2012* fed counts for 2007 for a given contigue text for clarification BMJ Open: first published as 10.1136/bmjopen-2016-012548 on 8 December 2016. Downloaded from http://bmjopen.bmj.com/ on June 12, 2025 at Agence Bibliographique de I Enseignement Superieur (ABES) . Protected by copyright, including for uses related to text and data mining, Al training, and similar technologies.

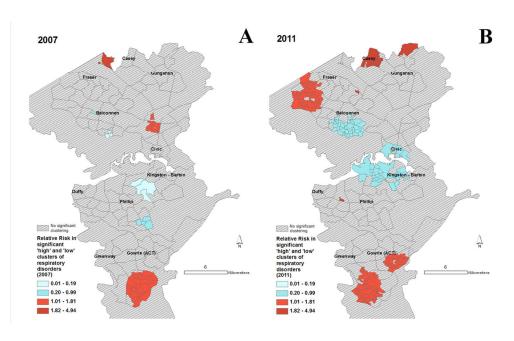


Fig 5: Spatial patterns of respiratory disease risk

Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with statistically significantly different risks of hospitalisation for respiratory diseases. Expected counts for 2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT

diseases (Figure 5) or were no 131x79mm (300 x 300 DPI)

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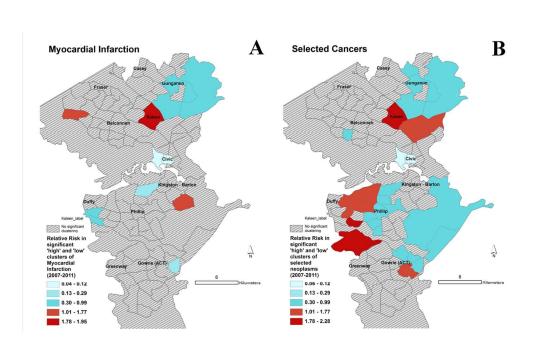


Fig 6: Spatial patterns of MI and cancer risk

Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT. BMJ Open: first published as 10.1136/bmjopen-2016-012548 on 8 December 2016. Downloaded from http://bmjopen.bmj.com/ on June 12, 2025 at Agence Bibliographique de I Enseignement Superieur (ABES) . Protected by copyright, including for uses related to text and data mining, Al training, and similar technologies.

problems with SaTScan is its p 131x79mm (300 x 300 DPI)

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Table S1.1: Summary of key individual level covariates in hospitalization data

Percent Female	53.55
Percent Married or in De Facto Relationship	48.74
Percent with Private insurance	87.96
Percent with hospital insurance	72.17
Median age	63 years

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	STI	ROBE 2007 (v4) Statement—Checklist of items that should be included in reports of cress-sectional studies 은 &	
Section/Topic	ltem #	Recommendation	Reported on page
Title and abstract	1	(a) Indicate the study's design with a commonly used term in the title or the abstract	2 Section 1
		لة من المن (b) Provide in the abstract an informative and balanced summary of what was done and what we found	2 Section 1
Introduction		2010 Janera	
Background/rationale	2	(a) Indicate the study's design with a commonly used term in the title or the abstract Image: State specific objectives, including any prespecified hypotheses	3
Objectives	3		3
Methods		Present key elements of study design early in the paper	
Study design	4	Present key elements of study design early in the paper	4
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, b b v-up, and data collection	4-7
Participants	6	(<i>a</i>) Give the eligibility criteria, and the sources and methods of selection of participants	4-7
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers diagnostic criteria, if	4-9
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	4-9
Bias	9	Describe any efforts to address potential sources of bias	10-13
Study size	10	Explain how the study size was arrived at	NA
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which applyings were chosen and why	4-9
Statistical methods	12	(a) Describe all statistical methods, including those used to control for confounding	10-13
		(b) Describe any methods used to examine subgroups and interactions	NA
		(c) Explain how missing data were addressed	5
			NA
		(d) If applicable, describe analytical methods taking account of sampling strategy iiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiii	2 Different models
Results			

graphique

		njopen-2016- BMJ Open BMJ Open	Page 3
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, exangined for eligibility,	4-8
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	NA
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information of magosures and potential confounders	4-8
		(b) Indicate number of participants with missing data for each variable of interest	4-8
Outcome data	15*	Report numbers of outcome events or summary measures	
Main results	16	(<i>a</i>) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision geg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	14-17
		interval). Make clear which confounders were adjusted for and why they were included (b) Report category boundaries when continuous variables were categorized 고급 효율	14-17
		(c) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful translating estimates of relative risk into absolute risk for a meaningful	NA
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyse	NA
Discussion			
Key results	18	Summarise key results with reference to study objectives	19
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	19-21
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	19-21
Generalisability	21	Discuss the generalisability (external validity) of the study results	19-21
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	22

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in centrol studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicinemorg/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.s observatement.org.

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Is Walk Score® associated with Hospital Admissions from Chronic Diseases? Evidence from a Cross Sectional study in a High Socio- Economic Status Australian City State

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Secondary Subject Heading:	Cardiovascular medicine, Public health
Keywords:	Geographical Information Systems, Chronic Diseases, Spatial Analysis, Walkability, Built Environment and Health, Australia

SCHOLARONE[™] Manuscripts

Is Walk Score[®] associated with Hospital Admissions from Chronic Diseases? Evidence from a Cross Sectional study in a High Socio- Economic Status Australian City State

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Abstract

OBJECTIVES: To explore patterns of non-communicable diseases (NCDs) in the Australian Capital Territory (ACT). To ascertain the effect of the neighbourhood built environmental features and especially walkability on health outcomes, specifically for hospital admissions from NCDs.

DESIGN: A cross-sectional analysis of public hospital episode data (2007-2013)

SETTING: Hospitalisations from the ACT, Australia at very small geographic areas.

PARTICIPANTS: Secondary data on 75,290 unique hospital episodes representing 39,851 patients that were admitted to ACT Hospitals from 2007 to 2013. No restrictions on age, sex or ethnicity.

MAIN EXPOSURE MEASURES: Geographic Information System derived or compatible measures of General Practitioner access, neighbourhood Socio Economic Status, alcohol access, exposure to traffic

and WalkScore® walkability.

MAIN OUTCOME MEASURES: Hospitalisations of circulatory diseases, specific endocrine, nutritional and metabolic diseases, respiratory diseases and specific cancers.

RESULTS: Geographic clusters with significant high and low risks of NCDs were found that displayed an overall geographic pattern of high risk in the outlying suburbs of the territory. Significant relationships between neighbourhood walkability as measured by Walk Score® and the likelihood of hospitalisation with a primary diagnosis of Myocardial Infarction (heart attack) were found. A possible relationship was also found with the likelihood of being hospitalised with four major lifestyle related cancers.

CONCLUSIONS: Our research augments the growing literature underscoring the relationships between the built environment and health outcomes. In addition it supports the importance of walkable neighbourhoods, as measured by Walk Score[®], for improved health.

1 2 3 1 4 5	Strengths and limitations of this study
6 2 7 2	• This is one of the few studies that investigate the relationship between walkability and
8 3 9	hospitalisations from heart disease and specifically myocardial infarction while simultaneously
10 4 11	investigating other chronic conditions and built/social environment drivers of health.
12 5 13	• This is the first study to report a significant relationship between heart attacks and walkability
14 6 15	(measured using Walk Score®).
16 17 7	• While there have been many walkability studies in low SES and demographically mixed areas this
18 19 8	is one of the few to report significant results from a relatively egalitarian, well educated, wealthy
20 9 21 9	region.
22 23 10	• The cross sectional nature of this study makes it difficult to infer causal relationships.
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28 Introduction

29 Background

Increasing rates of lifestyle-related non-communicable diseases (NCDs) such as cardiovascular disease and type 2 diabetes remain an area of public health concern in developed (and increasingly in developing) countries. In Australia, NCDs remain the predominant drivers of premature mortality and co-morbidity [1] .The Australian Capital Territory (ACT), is the wealthiestⁱ [2] and best educated state in Australia [3]. It has also been rated as one of the best places in the world to live by the Organisation for Economic Co-operation and Development [4], and has routinely been voted as the most liveable city in Australia [5]. In the annual "Australian Cities Liveability Survey" residents of Canberra have voted the city as being safe, affordable, having good employment and economic opportunities, having plenty of good schools/educational opportunities and an attractive natural environment with a wide range of opportunities for outdoor recreation activities [5]. In addition, there is a relative absence of heavy industry in ACT. Therefore, there is a general opinion that the ACT is an 'exceptional' city state in Australia with regard to its environment and planning. It follows therefore, that such a salubrious environment coupled with an educated population should encourage healthy lifestyle behaviours such as increased physical activity, which in turn should lead to significantly lower rates of lifestyle-related NCDs compared to the rest of Australia. Paradoxically, however, this expectation is not reflected in the ACTs burden of NCDs or lifestyle related risk factors relative to the rest of Australia. For example, adult prevalence of obesity/overweight in the ACT is 62.2% compared to an Australian average of 63.48%[6]. In addition rates of childhood obesity in the ACT are similar to those reported nationally. Furthermore, key environmental indices such as walkability in the ACT are not significantly different from the walkability in other major metropolitan cities in Australia [7]. While city level measures of walkability are of questionable value, our research, as outlined later in this paper, shows that at the very least there are significant variations in walkability within

53 the ACT, with the majority of suburbs being car dependent.

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55	Unlike many other cities, a high degree of government ownership and control over land has resulted in a
56	unique pattern of suburb development in the ACT [8]. The planning has attempted to mimic a geographic
57	"central place"[9] hierarchy with each suburb having its own suburb centre with shops and other
58	destinations. Suburbs are nested within larger districts. The ACT comprises 8 populated districts. Each
59	district has a central suburb, which is usually a very accessible, densely settled geographic central place
60	with access to various local destinations including services, shops and other amenities. Some of these
61	centres are also well served by public transport. Finally, in the centre of the ACT itself is the suburb of
62	'Civic', the central business district, with a very high degree of destination density. In spite of extensive
63	planning, many suburb centres have over the years, been affected with shop, school and other destination
64	closures [8] resulting in a reduction in the number of local amenities and reduced walkability. Thus,
65	planned and unplanned variations in the cityscape imply that residents are exposed to a variety of physical
66	environments which in turn may result in different health behaviours and resulting NCDs within the
67	geographic boundaries of the ACT.
68	
69	Investigation of the spatial patterns of key NCDs <i>within</i> the ACT and their associations with the physical
	investigation of the spatial patients of key NGDs want the ACT and their associations with the physical
70	and social environmental features can help identify environments that lead to adverse health outcomes
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	and social environmental features can help identify environments that lead to adverse health outcomes
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71 72	and social environmental features can help identify environments that lead to adverse health outcomes and highlight which design features of these environments are significantly associated with specific health outcomes. In addition to spatial variations in the built environment, an additional aspect that makes the
71 72 73	and social environmental features can help identify environments that lead to adverse health outcomes and highlight which design features of these environments are significantly associated with specific health outcomes. In addition to spatial variations in the built environment, an additional aspect that makes the ACT ideal for studying such relationships is the relatively high Socio Economic Status (SES) of the
71 72 73 74	and social environmental features can help identify environments that lead to adverse health outcomes and highlight which design features of these environments are significantly associated with specific health outcomes. In addition to spatial variations in the built environment, an additional aspect that makes the ACT ideal for studying such relationships is the relatively high Socio Economic Status (SES) of the majority of its residents [2, 3] though there are pockets of poverty [10]. It has been repeatedly
71 72 73 74 75	and social environmental features can help identify environments that lead to adverse health outcomes and highlight which design features of these environments are significantly associated with specific health outcomes. In addition to spatial variations in the built environment, an additional aspect that makes the ACT ideal for studying such relationships is the relatively high Socio Economic Status (SES) of the majority of its residents [2, 3] though there are pockets of poverty [10]. It has been repeatedly demonstrated, that if beneficial relationships do exist between the built environment and healthy
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71 72 73 74 75 76 77	and social environmental features can help identify environments that lead to adverse health outcomes and highlight which design features of these environments are significantly associated with specific health outcomes. In addition to spatial variations in the built environment, an additional aspect that makes the ACT ideal for studying such relationships is the relatively high Socio Economic Status (SES) of the majority of its residents [2, 3] though there are pockets of poverty [10]. It has been repeatedly demonstrated, that if beneficial relationships do exist between the built environment and healthy behaviours (and consequent health outcomes), they are more likely to be found in high SES locales such as the ACT [11, 12], since the relationship between environment and behaviour is confounded by a

81 individual level factors.

84 Methods

Conceptual Framework

We start with a theoretical basis of the well-known public health triad of environment, behaviours and health outcomes. Health outcomes are influenced by health behaviours, which in turn are associated with the environment. We summarize this in Figure 1. In Australia and elsewhere, a number of research papers have established the relationships between environment and behaviours (Link A – see figure 1) [14-18] or behaviours and health outcomes (Link B- see figure 1) [19, 20]. It logically follows that the environment is related to health outcomes through the individual lifestyle behavioural pathway. In addition, the built environment may directly influence health outcomes. For example, air pollution may be detrimental to respiratory and cardiovascular health [21], or perceptions on the environment may affect mental health [22]. However, research on this relationship (Link C-see figure 1) is limited, with most research, excepting a few [23, 24], focussing on outcomes related to sedentary health behaviours such as obesity [25, 26] and conditions directly related to obesity [27]. Our interest, therefore, was in investigating this relationship (Link C- figure 1), between aspects of the physical environment and the four major NCDs in the ACT: circulatory system diseases, specific cancers, Endocrine Nutritional and Metabolic Disorders (ENMDs) and respiratory disorders, using geocoded ACT hospitalisation data (from 2007 to 2013) and specific built environmental attributes.

- 102 Fig 1: Framework of relationships between environment, behaviours and health outcomes
- 103 -----

105 Investigating Relationships

106 To investigate relationships between the built environment and NCD-related hospital admissions, we

107 followed a combined exploratory-inferential approach. First, we asked "What are the spatial patterns of

108 the four key chronic conditions in the ACT?" This is addressed through exploratory mapping using

109 spatial cluster analysis. Second, we investigated relationships between various individual and

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environmental predictors such as neighbourhood walkability, traffic volume, and access to off-license
alcohol outlets and the key NCD-related hospital admissions in the ACT. In the next section, we explain
in detail the methods used to achieve this. The research was approved by the ACT Health Human

113 Research Ethics Committee (Ref.: ETH.11.14.310) on 8th December, 2014.

114

115 **Data**

116

117 Hospital Data

118 ACT Admitted Patients Data Collection (APDC) data were supplied by the ACT Health Directorate. This

119 consisted of 75,290 unique hospital episodes representing 39,851 patients admitted to all ACT public

120 hospitals between 1st January 2007 and 31st December 2013. Data were provided after ethics and other

121 data regulation requirements from the data custodian (The ACT Health Directorate) at

122 <u>HealthInfo@act.gov.au</u> had been met. The data were deemed sufficiently anonymous to not require

123 individual patient consent. Public hospitals capture around 80% of all hospitalisationsⁱⁱ in Australia [28].

124 The patient hospital admission data had Australian Census – Australian Bureau of Statistics (ABS) Mesh

125 Block (30 to 60 dwellings), Statistical Areas Level 1 (SA1s) (200-800 people) and SA2 (3,000-25,000

126 people) geocodes attached to them, therefore no additional geocoding was necessary. Each patient was

127 geocoded to their place of residence. Geocoding completeness [29] varied with geographical scale with

128 7,284 records missing at Mesh Block level, but only 949 missing at the SA2 level. A single hospital

129 episode included a primary diagnosis and up to a hundred other diagnoses. Primary diagnoses only have

130 been used in the analyses considered here

131

132 Selection of NCDs

133 The Global Burden of Disease 2010 study [30] and the Australia profile derived from this [31] have134 demonstrated unequivocally the dominance of NCDs in the burden of overall disease in Australia. In

- 135 2010, nine out of the top ten risk factors, accounting for almost 50% of the total disease burden (in
- 136 disability-adjusted life years), were lifestyle-related. The four broad NCD categories included in this study

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137	were chosen as they currently contribute the greatest burden in terms of health care resource cost in the
138	ACT.
139	
140	While all hospitalisations for four ICD-10 codes: E, C, J and I, were provided, we divided the data into
141	specific sub-codes, removing conditions with obvious genetic or familial drivers (i.e. not directly related to
142	lifestyle risk). Note that these ICD-10 codes could have been a primary or an additional diagnosis. Each
143	condition was analysed separately and with comorbidity. The subsets of ICD-10 codes used in our
144	analyses were:
145	A) Circulatory Diseases: all diseases of the circulatory system i.e. ICD 10 (I00-I99) code 'I' (circulatory
146	system diseases or CSDs). However, we also created a data subset of hospital admissions with a primary
147	diagnosis for Myocardial Infarction (MI) and subsequent infarctions (ICD 10 codes I21 and I22
148	respectively). MI or heart attack represents a serious and sudden event generally requiring immediate
149	hospitalisation.
150	B) Cancers: We included cancers of the breast 'C50', colorectal cancers 'C18-C21', Endometrial Cancer
151	'C54.1' and lung cancers 'C33-C34'. These cancers have been associated with lifestyle risk factors [32].
152	C) Endocrine, Nutritional and Metabolic Diseases (ENMDs) - E10-E16 and E-66.
153	D) Diseases of the Respiratory system – J00-J99 i.e. all diseases of the respiratory system.
154	Table 1 describes the overall episodes of hospitalisation related to NCDs.

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155 **Table 1:** Total hospitalisations for each non-communicable disease category by year^a

Year	Specific	Respiratory	CSD	МІ	ENMD	Any of the four
	cancers	system				major NCDs
2007	573	3381	4992	369	1673	8051
2008	661	3762	5314	415	1618	8796
2009	709	3639	5492	528	1411	8913
2010	680	3646	5126	516	1075	8563
2011	716	4203	5379	530	793 ⁺	9316
2012	714	4405	5458	543	1498	9453
2013	704	4273	5391	491	2041	9234

^a Some hospitalisations were for multiple conditions, thus totals with any of the four major NCDs were less than the sum of

single NCDs; CSD-circulatory system disease, MI-myocardial infarction; ENMD-endocrine, nutritional and metabolic diseases;

158 NCD-non-communicable disease; + The numbers of ENMDs in 2011 are anomalously low, the reason for this is not known.

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Of these conditions CSDs and ENMDs are known to be associated with a sedentary lifestyle, as is obesity, colorectal and endometrial cancer [32]. Lung cancers and respiratory diseases are driven to a great extent by smoking and air quality. For statistical modelling and analysis, we used all hospital admission episodes (2007-2013), but for spatial mapping we further sub-divided the hospital data to the years 2007 and 2011 because these link to the national censuses (2006 and 2011) with available reference population data. A number of individual level covariates were included in the hospital data: gender, age (years), marital status, private insurance and hospital insurance. The last two variables may serve as proxy measures of SES. The covariates are summarized in Appendix S1 Table S1.1. **Population Data** In addition to the above data, population data were required for mapping rates of hospital admission. The smallest geography at which Australian demographic data (for example age, gender, SES) are released is the Statistical Area 1 (with an average of 500 people). SA1 is therefore a relatively small geographic area at which NCD-related hospital admission rates could be mapped. However, there were relatively smaller numbers of neoplasm and MI cases (Table 1) hence these conditions required a larger geography, - the SA2 for mapping because rates based on small numbers of expected cases are unstable and have large confidence intervals. In this study the term suburb is used to define the spatial boundary defined by the ABS in 2011 as SA2. Therefore we aggregated up to the Statistical Area 2 (SA2 - suburb) level. In addition, while ENMDs and CSDs can be mapped at SA1s annually given their large annual numbers in the ACT (Table 1), aggregate sums over multiple years were used for MI and neoplasms. Australian census output geographies changed significantly between 2006 and 2011. While, there are minimal differences between 2011 SA2 geographies and their 2006 counterpart Statistical Local Areas (SLAs) in the ACT [33], there was significant spatial mismatch between 2011 SA1s and their 2006

counterpart in the census hierarchy- Collection Districts(CDs). Thus, when mapping by SA1s or CDs (ENMDs, respiratory diseases and CSDs), we show separate maps for 2006 and 2011. Age specific 2011 population counts at SA1s and 2006 counts at CDs were obtained from the ABS. For SA2 level maps of neoplasms and MI, counts of expected numbers of cases for the years 2007-2011 were required. Age specific 2011 population counts and 2006 population counts were obtained at SA2s/SLAs. To obtain the age distribution for the intermediate years (2007-2011) at SA2s, we linearly interpolated the numbers in each SA2/age group between 2006-2011. This generated the fraction of people in each age group in a given year in a SA2. We then used an indirect age standardization technique to calculate annual expected numbers of cases of an NCD using the annual age distributed ACT population as the standard population [34]. Expected annual numbers were also calculated for the CD, SA1 and SA2 data. We used 2006 expected counts when mapping 2007 hospitalisation data since 2007 SA1 or CD population counts were not available. **Environmental Data** As summarised in Figure 1, we wanted to investigate relationships between various built environmental attributes and health events ((hospital admissions). A number of environmental covariates were collected, collated and/or created in-house by the authors. Our choices of environmental drivers were informed by

- 206 previous research but also constrained by the available data. For example, we did not have geocoded data
- 207 for food outlets so could not explore any relationships between hospital admissions and the food
- 208 environment. The environmental indices that were available are described below:
- Walkability: Walking is the most prevalent form of physical activity in the population [35,
 36]. The degree of neighbourhood walkability predicts the degree of walking[37]. We
 measured the physical activity environment through suburb level walkability. While other
 aspects of the physical activity environment such as access to parks and leisure/exercise
 centres are also important, the walking network remains one of the most important built
 environmental attributes for overall physical activity [13]. Walk Score[®] is a measure of
 walkability produced by a United States based company that has been validated [37] and has

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2 3	216	been utilized in a number of public health studies in the United States. In the Australian
4 5	217	context, it has been found to have strong relationships with walking for transport in a recent
6 7	218	study [14], though relationships with health outcomes have not previously been found [23].
8 9	219	Walk Score® is a composite measure of destination density. The scores are normalized to a 0
10 11	220	to 100 scale, with 0 being the lowest walkability and 100 being the highest. A five scale
12 13	221	categorization is used; "Walkers Paradise" (Walk Score® 90-100), "Very Walkable" (70-89),
14 15	222	"Somewhat walkable" (50 to 69), "Car-dependent" (25 to 49)" and "Car Dependent" (0-24)
16 17	223	by the developers of Walk Score [®] [38] and these categories have been used by other
18 19	224	researchers [16]. Walk Scores® for ACT suburbs/SA2s were obtained from the Walk
20 21	225	Score [®] website [38]. A map of Walk Scores [®] at ACT suburbs is provided in Figure 2.
22 23	226	
24 25	227	Fig 2: Map of five categories of Walk Score® by ACT suburbs
26 27	228	The five categories are "Walkers Paradise" (Walk Score® 90-100), "Very Walkable" (70-89),
28	229	"Somewhat walkable" (50 to 69), "Car-dependent" (25 to 49)" and "Car Dependent" (0-24)
29 30	230	
31 32	231	
33 34	232	2. Access to General Practitioners: access to primary care is an important predictor of
35 36	233	admittance into tertiary facilities [39, 40]. Access to General Practitioners (GPs) is related to
37 38	234	better health management and lesser use of hospital services [39, 41]. We created an access
39 40	235	measure by drawing a circular buffer around the Mesh Blocks of the patients in the
41 42 43	236	hospitalisation data. The circular buffers around the Mesh Blocks adaptively grew to
43 44 45	237	different sizes, with each buffer growing until a total of 1000 people were included in the
46 47	238	circle. The numbers of GP clinics in the buffer circles were then summed to provide an
47 48 49	239	approximate measure of access as the number of GP clinics per thousand persons. GP clinic
49 50 51	240	data for 2010 were provided by the ACT Medicare Local, while underlying 2011 census
52 53	241	population data were obtained from the ABS.
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244	3.	Neighbourhood SES: is a well-established marker of social environment including crime and
245		social cohesion and a mature literature supports the relationship between neighbourhood
246		SES and a range of health outcomes [42]. The Socio-Economic Indexes for Areas (SEIFA)
247		are indices of area level of Socio-Economic Status in Australia developed by the ABS. The
248		Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD) is one such index
249		that measures both advantage and disadvantage. The index was created by incorporating a
250		number of measures including percent unemployed, car ownership and percent disabled.
251		SA1 level IRSAD scores for 2011, the finest resolution at which they are available were
252		incorporated into these analyses.
253		
254	4.	Alcohol outlets: along with the food environment alcohol outlets are powerful predictors of
255		lifestyle-related health outcomes [43]. While the food environment is best represented by
256		summary measures of access to a range of food outlets, we did not have access to an
257		integrated, clean, geocoded dataset of food outlet locations in the ACT for this study (see
258		Discussion). Easy access to alcohol has been related to a number of negative health and
259		social outcomes [44, 45], and we have used a measure of alcohol access in our analyses. A list
260		of all licensed off-license liquor outlets was obtained from the ACT Department of
261		Regulatory Services [46] and geocoded to SA1 level. Off-license outlets are licensed to sell
262		alcohol, but alcohol cannot be consumed within premises, examples of which include
263		supermarkets and bottle shops. The mean road network distance to off-license liquor outlets
264		from each patient SA1 centroid served as a measure of access to alcohol.
265		
266	5.	Road Traffic Exposure: The presence of road traffic can act as an impediment to physical
267		activity in a neighbourhood environment [47]. We thus created a measure of exposure to

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road traffic using methods published earlier [47].

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271 Analysis

Spatial patterning of hospital admissions related to NCDs were explored using a cluster detection tool,
the Spatial Scan Statistic [48]. Monte Carlo regression was then employed to investigate relationships
between NCD-related hospitalisations and built environmental factors.[29, 49]. Finally, a negative
binominal was also employed to test the relationship between NCDs and built environmental factors.

276

277 Exploratory Spatial Scan Statistic

Exploratory methods allow us to generate hypotheses about relationships (Link C, Figure 1) by visually
correlating significant spatial patterns of NCD-related hospital admissions with spatial patterns of
environmental variables. We used the well validated and robust Spatial Scan Statistic to investigate
significant spatial patterns [48, 50, 51]. This method asks "What area or *what combination of areas* is most
likely to have a statistically significantly 'high' or a significantly 'low' risk relative to areas outside the
combination of areas?" This would be framed as a "cluster detection problem" in the spatial
epidemiology literature [48].

285

286 The Spatial Scan Statistic was implemented using the SaTScan software. This method implements a single 287 maximum likelihood based hypothesis test over geographic space to identify the regions where the 288 distribution of cases relative to controls/population (or the expected number of cases) is most likely to be 289 consistent with a significant excess risk. To implement this, SaTScan identified candidate clusters, which 290 were circles of increasing radii, bound by a maximum population threshold radius (set here to 5% of the 291 population), centred on pre-specified locations such as SA1 centroids. The size of the cluster is 292 sometimes sensitive to the threshold radius [52]. The 5% threshold represents around a few hundred 293 expected cases of most NCDs, and is sensitive enough to delineate small clusters, an early goal in our data 294 exploration and analysis. 295 Over many candidate clusters SaTScan maximizes the likelihood ratio, given by

296 LLR=O*ln(O/E)+O*ln((n-O)/(n-E))

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Where, LLR represents the logarithm of the likelihood ratio, O are observed cases, E are expected cases, and n is the total number of cases in the entire region (ACT). The likelihood formula assumes that NCD cases are distributed as a Poisson random variable and the likelihood ratio is compared to simulated likelihood ratios generated from 999 Monte Carlo randomizations of the data to assess statistical significance. The area that has the highest likelihood value (or the lowest p value) is the primary cluster. If both low and high risk clusters are searched for then the most likely (high and low) clusters will be identified and published by the software. Secondary or less likely clusters may also be reported. In our analyses we restricted our results to primary or secondary clusters with a significant p value. Relative risks at the significant clusters were reported as: (risk inside the cluster)/(risk outside the cluster.) SaTScan analyses were implemented for CSDs and respiratory diseases at the SA1 scale for 2011 and CD scale for 2007. Because of an unexplained anomalously low number of hospitalisations for ENMDs in 2011 (Table 1), we scanned 2012 SA1 and 2007 CD ENMD data. Due to lower event rates, MI and selected cancers were analysed at the SA2 scale for the entire aggregated 2007-2011 period. Thus, SA2 level observed and expected numbers were summed for the entire 5 year period 2007-2011. Results were mapped using ArcGIS 10.1. Associations between built environment factors and hospital admission rates We used two different models to investigate the relationships between the various NCD-related hospital events and built environment characteristics. The hospital admission data were complex, with multiple cross classifications and nesting. For example, each person in the data could be hospitalised multiple times (nesting of hospitalisation episodes within people), people were nested in geographic neighbourhoods such as suburbs, and the temporal nature of the data, implies likely temporal trends and seasonal patterns. In addition, the distributions of a number of predictors such as suburb level Walk Score® or GP density were not normal, which would render traditional linear models unusable, or require complex statistical transformations and/or models. To overcome this problem we first modelled

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relationships using a robust method: Monte Carlo logistic regression [29, 49]. The approach was as follows: 1. Randomly sample 50% of the data 2. Fit logistic regressions (or any other model to be tested) to estimate best explanatory model, store parameter estimates: intercept and slope values 3. Repeat steps 1 and 2, N times (In our simulations N=1000) 4. Calculate mean and 95% confidence intervals for estimated model parameters from stored values in step 2. We utilized logistic regressions as our explanatory model, with each hospitalisation event with a primary diagnosis of respiratory diseases as the control condition. The dependent variable was a hospitalisation event (1/0) with a primary diagnosis of each of the NCDs described in the data section, - cancers, CSDs, MI, ENMDs and comorbids. Separate models were run for each of MI, CSDs, specific neoplasms, ENMDs and comorbids. Respiratory diseases were chosen as the control condition because the drivers of respiratory disorders, with the exception of smoking, generally differ from the environmental drivers of the other three conditions. (While ideally we would have liked to use all hospitalisations as controls, these data were not available at the time of analysis). When modelling neoplasms, since lung cancers have somewhat different environmental drivers than the remaining cancers, we ran the model with and without lung cancer. We also attempted to model hospitalisations with comorbid CSDs, specific neoplasms, ENMDs and respiratory diseases conditions by coding hospitalisation with more than one condition as 1, and the rest 0. The independent variables in these models were: sex, age, marital status, payment with private insurance (yes/no) of the person hospitalised. In addition ecological level independent variables (described in the data section) include the hospitalised person's access to GPs, neighbourhood walk score, IRSAD score, access to alcohol and logged traffic exposure. Finally, for NCDs with significant environmental correlates in the Monte Carlo model we also modelled the total number of hospitalisation events of a given condition in a given suburb as a function of counts of different predictors. The models can be written as:

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Y _j ~	ν Negbin(μ _j , κ)
μ _j =	$e^{(\beta 0 + \sum_k \beta_k x_{jk})}$

350	Where Y_j is the total count of a given condition in suburb j and x_{jk} is the count of the k'th predictor in
351	the j'th suburb, for example, - the total number of insured patient hospitalisations in a suburb or total
352	number of female patient hospitalisations in a suburb. Y _j was considered to be negative binomially
353	distributed with mean μ_j and variance κ . A negative binomial model was used after it was found that the
354	data were overdispersed, rendering a Poisson model unsuitable. The mean μ_j or suburb level count of a
355	given outcome was modelled as an exponential function of an intercept term β_0 and a slopes term β_k .
356	These models require aggregate counts or summaries at the suburb level, and variables were recoded to
357	satisfy this requirement. Thus, for example, discrete variables such as the marital status of a hospitalised
358	person $(1/0)$ translated to the total number of hospitalisations of married people in a given suburb.
359	Continuous variables were similarly recoded, such as the number of hospitalisations of people in the
360	topmost quartile of traffic exposure, number of hospitalisations of people in lowest decile of IRSAD,
361	number of hospitalisations of people with good GP Access and so on. People with a GP density of 1 or
362	more in their immediate buffer neighbourhood were considered to have good access.
363	The models were implemented using R and Stata.
364	
365	The models were implemented using R and Stata. Results Figures 3 to 6 display the results of the Spatial Scan Statistic analyses. We report all significant clusters of
366	Figures 3 to 6 display the results of the Spatial Scan Statistic analyses. We report all significant clusters of

Results

Figures 3 to 6 display the results of the Spatial Scan Statistic analyses. We report all significant clusters of both 'high' and 'low' risk. Reporting all significant clusters instead of the "most likely" cluster has been shown to enhance exploratory analyses [52, 53]. The scan results displayed a general trend of higher risk of hospital admissions in the outer suburbs and lower risk in the inner suburbs. Thus, the suburbs of Civic and Kingston-Barton either had significantly lower risk of CSDs (Figure 3), MI (Figure 6) and respiratory diseases (Figure 5) or were not significantly different clusters (Figures 3-6). While maps of all

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372	CSDs showed some random variation from 2007 to 2011, sections of West Belconnen around Fraser and
373	areas south of Gowrie; and north of Gunghalin showed consistent high risk of CSDs (Figure 3). Some of
374	these areas also showed consistent high risks of ENM diseases (Figure 4).
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376	
377	Fig 3: Spatial patterns of CSD risk
378	Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with
379 380	statistically significantly different risks of hospitalisation for all CSDs. Expected counts for 2007 were
380 381	calculated using 2006 census populations. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT.
382	
383	Fig 4: Spatial patterns of ENMD risk
384 385	Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2012* with
386	statistically significantly different risks of hospitalisation for selected ENMDs. Expected counts for 2007
387	were calculated using 2006 census populations and census 2011 for 2012. Relative risk for a given
388 389	contiguous cluster was calculated relative to the risk in the rest of the ACT. * see text for clarification
390	Fig 5: Spatial patterns of respiratory disease risk
391	Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with
392	statistically significantly different risks of hospitalisation for respiratory diseases. Expected counts for
393	2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was
394	calculated relative to the risk in the rest of the ACT
395 396	
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398	The spatial patterns of MI and cancer risk (Figure 5) did not show a consistent pattern though we can se
399	that highly walkable suburbs such as Civic, Kingston-Barton and Belconnen were either low risk (Relativ
400	Risk/RR <0.13) clusters or were non-significant clusters. One of the recognized problems with SaTScar
401	is its propensity at larger geographic scales to detect large low risk clusters in rural, sparsely populated
402	areas. Thus, areas North East of Gungahlin, and some areas south east of Kingston-Barton appear as lo
403	risk clusters, which in reality have very few residents (Figure 6).
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Fig 6: Spatial patterns of MI and cancer risk

Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT.

- The results of Monte Carlo logistic regressions showed significant relationships between suburb level
- Walk Score[®] and the risk of Myocardial Infarction (Table 2). Specifically there was a 4% 1.04 (95% CI:
- 1.01, 1.07) increased odds of being hospitalised for a heart attack from living in a neighbourhood that is
- not a "Walker's Paradise". Similarly, there was a significant progressively increasing risk of being
- hospitalised with cancer when living in increasingly less walkable suburbs. When lung cancers were
- removed from the set of four cancers (not shown), the effect sizes remained the same, but the confidence
- intervals widened, becoming marginally non-significant. This probably indicates that the relationship with
- neoplasms are likely valid, but the regressions are underpowered due to small numbers.

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Predictor	CSD	МІ	ENMD	Selected Neoplasms	More than one comorbio NCD
Individual Level Variables					
(Intercept)	1.09 (0.98 , 1.21)	0.99 (0.95 , 1.02)	1.14 (1.02 , 1.27)	0.85 (0.81 , 0.9)	0.02 (0.00, 0.13)
Female	0.95 (0.94 , 0.96)	0.97 (0.97 <i>,</i> 0.98)	0.95 (0.94 , 0.96)	1.09 (1.08 , 1.10)	0.86 (0.83 , 0.90)
Age in years	1.01 (1.01 , 1.01)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.04 (1.04 , 1.04)
Married	1.11 (1.1 , 1.12)	1.02 (1.01 , 1.02)	1.04 (1.03 , 1.05)	1.06 (1.05 , 1.07)	0.93 (0.89 , 0.98)
Paid with private insurance	0.99 (0.98 , 1.01)	1.06 (1.05 , 1.07)	0.99 (0.97 , 1.01)	1.08 (1.07 , 1.10)	0.98 (0.91 , 1.06)
Has hospital insurance	1.02 (1.01 , 1.03)	0.98 (0.97 <i>,</i> 0.99)	0.99 (0.98 , 1.01)	0.97 (0.96 , 0.98)	0.90 (0.84 , 0.95)
Ecological Variables					
Access to GP clinic	1.00 (1.00 , 1.01)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	0.99 (0.97 , 1.01)
Walk Score [®]					
Reference: Walker's paradise (Score 90 to 100) [×]					
Very walkable (Score 70 to 89) or Somewhat walkable (Score 50 to 69)	1.02 (0.92 , 1.13)	1.04 (1.01 , 1.07)	1.07 (0.97 , 1.19)	1.06 (1.01 , 1.12)	1.87 (0.37 , 9.4)
Car-dependent (Score 25 to 49) or Car dependent (Score 0 to 24)	1.03 (0.93 , 1.14)	1.04 (1.01 , 1.07)	1.09 (0.98 , 1.2)	1.07 (1.01 , 1.12)	2.02 (0.04 , 10.24)
IRSAD score	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)
Mean distance to off-license alcohol outlet Log traffic exposure	1.00 (0.99 , 1.01) 1.00 (1.00 , 1.00)	1.00 (0.99 , 1.01) 1.00 (1.00 , 1.00)	1.00 (0.99 , 1.01) 1.00 (1.00 , 1 .00)	1.00(0.99 , 1.01) 1.00 (1.00 , 1.00)	0.92 (0.88, 0.96) 1.00 (1.00, 1.00)
Pseudo R ^{2 a}	16.83	95.5	3.54	22.3	10.16

* Significant effects in bold. Significance levels were not computed for Monte Carlo estimates; X Walker's Paradise is the reference category while the two car dependent and two walkable categories are aggregated,^a Pseudo R² is a measure of the amount of variation explained by the model; CI-95% confidence interval; NCD-non-communicable diseases; CSD-circulatory system diseases; MI- myocardial infarction; ENMD-endocrine, nutritional and metabolic diseases; GP-General Practice, IRSAD-Index of Relative Socioeconomic Advantage and Disadvantage; Total number of hospitalisation events: N=75,290

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The relationships were supported by the negative binomial model (Table 3). For example there are 4% less hospitalisations with myocardial infractions from neighbourhoods that are a walker's paradise relative to car dependent neighbourhoods. Somewhat counter-intuitive, relationships with hospital admissions from neoplasms were found, where those living in a poorer neighborhood or having less access to GPs decreased the likelihood of a hospitalisation which may suggest the potential for missed diagnoses. Being female was protective for circulatory disease, myocardial infarction, ENMD or hospitalisation with more than one condition but was a risk factor for selected neoplasms (Tables 2, 3). Being married (or in a de-facto relationship) increased the risk of being hospitalised with any condition but decreased the risk of being hospitalised with multiple conditions (Tables 2, 3). In Australia, while public hospital services are free, patients may have the choice of accessing private services for a fee, usually paid through insurance. Paying with private insurance was positively associated with MI hospitalisation or hospitalisation with selected neoplasms. Overall, the results of the regressions agreed with results of exploratory mapping - that is, the outlying low walkability suburbs have higher rates of key NCD-related hospital admission.

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Table 3: Summary of negative exponentiated binomial model fit coefficients (CI)^a

Number of hospitalisations of :	МІ	Selected Neoplasms
Females	1.0005 (0.9978 , 1.0032)	1.0007 (0.9964 , 1.005)
Married people	1.0032 (1.0016 <i>,</i> 1.0049)**	1.0036 (1.0004 , 1.0068) [.]
Paid with private health insurance	1.0032 (0.9976 , 1.0087)	1.0047 (0.9953 , 1.0141)
People with with hospital insurance	0.9958 (0.9924 , 0.9992)*	0.9952 (0.9891 , 1.0014)
People within 1 km distance to off-license alcohol outlets	0.9999 (0.9995 , 1.0003)	1.0001 (0.9992 , 1.0009)
People 44 and younger	0.9980 (0.9927 , 1.0033)	0.9829 (0.9691 , 0.9971)
People 45 to 64	0.9980 (0.9923 , 1.0038)	0.9885 (0.9738, 1.0034)
People 65 and over	0.9997 (0.9943 , 1.0050)	0.9856 (0.9715 , 0.9999)
People with good GP Access	1.0020 (0.9963 , 1.0077)	1.0172 (1.0033 , 1.0313)
People living in suburbs that are a "Walker's Paradise"	0.9545 (0.9166 , 0.9782)*	0.9048 (0.7944 , 0.9583)
People in "Very Walkable" or "Somewhat Walkable" suburbs	0.9999 (0.9997 , 1.0002)	1.0002 (0.9997, 1.0008)
People in lowest decile of IRSAD	1.0000 (0.9994 , 1.0007)	0.9981 (0.9965 , 0.9996)
People in topmost quartile of traffic exposure	0.9999 (0.9995 , 1.0003)	0.9995 (0.9986 , 1.0004)

^a Significant effects in bold - Key: p<0.001 **, p<0.05 *, p=0.05⁺

CI-95% confidence interval; MI-myocardial infarction; GP-General Practice ;IRSAD-Index of Relative Socioeconomic Advantage and Disadvantage; Number of suburbs=90 Ch Only

421 Discussion

We found that Walk Score® was significantly associated with hospital admission for MI. The spatial patterns of MI admission rates and Walk Score® supported this finding. Thus, individuals residing in a neighbourhood considered a "Walker's Paradise" (e.g. Civic) have significantly lower risks of admission for MI after adjustment for age, gender, marital status and insurance status. A similar relationship existed with certain neoplasms though further investigation is required to support this finding. The highest risks of neoplasms and MI admission rates were found in Kambah (Walk Score®: 28) and Kaleen (Walk Score[®]: 39) which were classified as 'Car Dependent' by Walk Score[®]. While a number of studies have shown that Walk Score[®] is related to walking for recreation and transportation [14-16, 37] ours is one of the few studies [23, 24] that showed a significant relationship between Walk Score® and hospital admissions. Our analyses utilized suburb level Walk Scores®. It is known that there are significant differences in walkability within suburbs, and therefore individual residential level Walk Scores® could capture more of the variation in walkability in the ACT, and perhaps help in obtaining more robust estimates of the

relationships between key NCD-related hospital admission and walkability. Walk Score[®] itself, has been criticized by some researchers as a measure of walkability though some of these criticisms, - such as the use of "as the crow flies" distance have been rectified in the newer versions of Walk Score[®], which we have used [38]. Another shortcoming with the Walk Score[®] and other environmental data used in these analyses is that they are from a single time point over the analysis period. While theoretically temporal synchronisation between the environmental data and the health data is ideal, accessing archived spatial datasets for different time periods of interest was not possible in a reasonable timeframe for this study.

442 Our data are from public hospital data, and we did not have access to private hospital data. While there is 443 a possibility that this may cause biases, public hospitalisations cover the majority of hospitalisations in the 444 ACT, and therefore are mostly representative of hospitalisations in this population [28]. Nevertheless, it is 445 possible that there are suburb level (or smaller area) variations in the proportion of private hospital 446 admissions relative to public hospital admissions. This may cause biases the extent of which are not

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known. Some of the areas with consistent low risk, such as Civic and Kingston-Barton (at the centre of the ACT) are areas with high residential density, easy access to shops and public transport. These areas also tend to draw a higher proportion of individuals who are younger and mobile, and are less likely to be hospitalised for any condition whatsoever. Since our regression models do not incorporate underlying population data, it is possible that variations in area level populations may affect our analyses. Nevertheless, exploratory cluster mapping *does* incorporate underlying population and we note that areas such as Civic, Phillip, Kingston-Barton were generally low risk clusters. Therefore the relationships are unlikely to be biased by population heterogeneity in hospitalisation rates. A recent similar study from Australia found no significant association between Walk Score® and the likelihood of Ischemic Heart Disease [23]. There could be multiple reasons for this, including the fact that the Walk Score® at geographic centroids of SLAs were used to summarize the Walk Score® in a given SLA. Since there is considerable variation of Walk Score[®] within an SLA, a geography much larger in size than SA2s in the aforesaid study, using centroid Walk Scores® may not be appropriate. In contrast we used an SA2/Suburb level Walk Score[®], which represents the average Walk Score[®] at the suburb level. Another reason as to why significant associations were not found in the study [23] could be the outcome investigated, - Ischaemic Heart Disease (IHD). This condition, like CSD, may remain undiagnosed in the population resulting in a hospitalisation dataset that is not representative of the true patterns of the condition in the population. MI, which is a severe acute outcome of undiagnosed IHD or CSD, is less likely to suffer from diagnostic bias. To our knowledge, at least one other study, in this case reporting results from the United States, has reported an association between mixed land use, better access to fitness facilities and a lower risk of coronary heart disease in low income women [24]. The local government area of ACT is high SES and relatively egalitarian being at the middle of the income inequality league relative to other local governments in Australia [54]. Car ownership in the ACT (603 per 1000 people) is well above the Australian average (568 per thousand) with only two states, Victoria and South Australia having higher ownership rates. In addition, public and active transport modes of travel to work are less popular in the ACT compared to other capital cities [55]. The combination of high SES, low walkability and high car ownership is known to discourage walking (recreational or transportation walking) [11, 12], which in turn may influence the risk of heart disease or cancer, as demonstrated in this

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study. It is possible that cars may enable informed individuals to shop for healthy foods, but the food environment beyond alcohol is not explored in this study. Incorporating the food environment in our analyses is an area of future work. Further work will include additional environmental measures (for example, air quality and crime will be included in the next phase), further refinement of indices (for example, mix of food outlets, nutritional quality of food available), closer analysis of the metric and distributional properties of each measure and better quality data on individual behaviours. In addition, future research should assess whether the present findings are replicated in similar, as well as in different, populations and settings.

This study utilizes an ecological cross sectional design which may generate bias. In addition patients could have a condition and not be hospitalised (e.g. death from MI before hospitalisation). Cancer registries could supply better quality and more comprehensive data than hospitalisation from neoplasms. Another limitation of our study is that we used respiratory disorders as our control condition in the regressions. This is because the drivers of respiratory conditions are generally different from the drivers of heart attacks, ENMDs etc. While our data, which were limited to the four conditions, constrained the analyses to this specific control, future analyses will attempt to incorporate all hospitalisations as control condition. We showed that there are relationships between walkability as measured by Walk Score and key NCDs providing support of the logical link between environment, behaviours and health outcomes (Figure 1: Link C). Nevertheless, we remain interested in investigating Link A, the relationship between environment and behaviours. Since 2013 data on life-style risk behaviours at the suburb level such as smoking/alcohol and BMI have become available through the ACT Adult health survey. Incorporation of these data into further analyses remains an area of future exploration. Furthermore, if individual level address information of the survey respondents were available, this would allow a more precise and accurate investigation of the effects of the built environment on lifestyle risk behaviours and NCDs.

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502	Our analyses form a unique and systematic investigation into the effect of built environment and
503	consequent NCD-related hospital admissions. This research highlights the significant role that walkability,
504	plays in health and in use of health care resources i.e. hospitals. While this research could have significant
505	bearings on local policymaking, it also captures a niche in the broader built environment and health
506	literature with its investigation of relationships between the built environment and health outcomes.
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516	The opinions expressed in this paper are those of the authors and not those of the funding body. The
517	funding body played no part in the design of the study, in the analyses and the interpretation of findings,
518	and in the decision to submit the manuscript as a publication.
519 520	Supporting Information
521	Appendix S1: Summary of key individual level covariates in hospitalisation data
522	
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527	

ŗ	528	Competing Interests			
Į	529				
Į.	530	None declared			
	531				
	532	Contributions			
ŗ	533				
ŗ	534	SM, VL and TC implemented the data cleaning, statistical analyses and the writing. RD, HP and BC			
ŗ	535	provided analytical oversight, reviewed the manuscript and helped with the writing.			
	536				
		Data Sharing Statement			
	537	Data Sharing Statement			
	538				
	539	The hospital data were provided after ethics and other data regulation requirements from the data			
	540	custodian at <u>HealthInfo@act.gov.au</u> . Anyone with the appropriate ethics clearances can request the data			
	541	custodian for the data.			
I.	542				
ŗ	543	Ethics statement			
I S	544				
ſ	545	The research was approved by the ACT Health Human Research Ethics Committee (Ref.:			
	546	ETH.11.14.310) on 8th December, 2014.			
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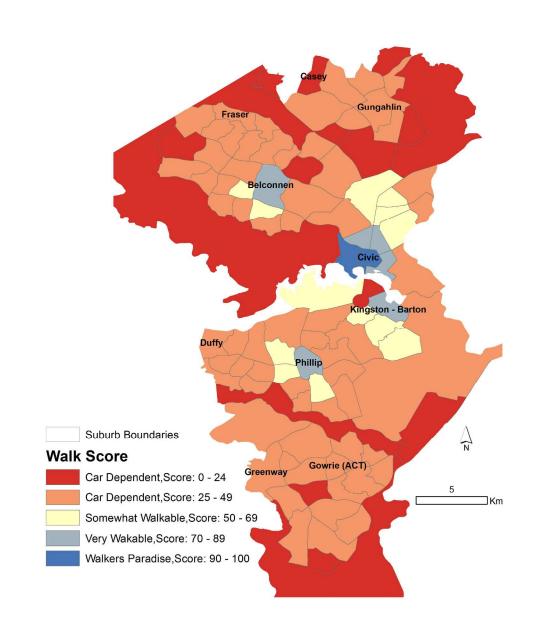
672 53. Boscoe FP, McLaughlin C, Schymura MJ, Kielb CL. Visualization of the spatial scan	statistic
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- 673 using nested circles. Health & Place. 2003;9(3):273-7.
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 - 675 Boom: 2001–11. Australian Geographer. 2015;46(2):203-16.
 - 676 ABS. 4102.0 - Australian Social Trends, July 2013 - Car nation 2014. 55.
- 677

11-govern. bish data . " This is a national statistic. The ACT government does not collect and/or publish private hospitalisation data, but it is unlikely to differ significantly, since states that do publish data report similar fractions of public and private hospitalisations.

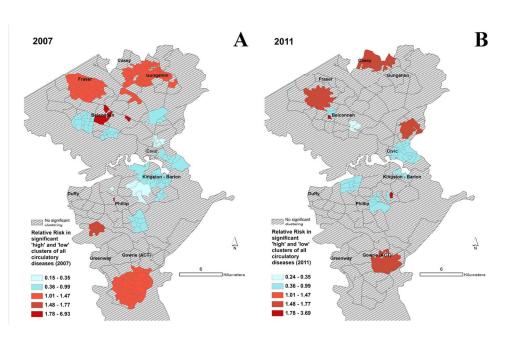
¹ Median Household income/week in 2011-12 was AUD 2,124 compared to a national average of AUD 1,612

Environment		Behaviours		Hea	lth Outcomes
Service Environment:			Li	nk B	
Access to Primary Care	Link A				
		Physical activit	Υ		
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Environment: Walkability		Alcohol			
		Aconor			e Nutritional and bolic diseases
Social Environment:		Smoking		Ivieta	bolic diseases
Measure of Neighbourhood Socio-		Social Participatio	on		
Economic Status				Sele	cted Cancers
Nutrition					
Environment: Access to alcohol outlets				Respirato	ory system diseases
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Exposure Environment:					
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Map of five categories of Walk Score® by ACT suburbs.The five categories are "Walkers Paradise" (Walk Score® 90-100), "Very Walkable" (70-89), "Somewhat walkable" (50 to 69), "Car-dependent" (25 to 49)" and "Car Dependent" (0-24) "Somewhat walkable" (50 to

186x241mm (300 x 300 DPI)





Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with statistically significantly different risks of hospitalisation for all CSDs. Expected counts for 2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT.

While maps of all CSDs showed 131x79mm (300 x 300 DPI)

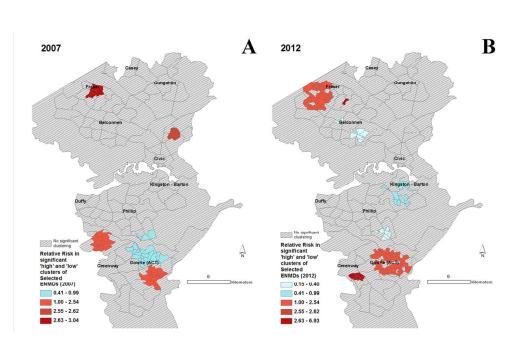


Fig 4: Spatial patterns of ENMD risk

Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2012* with statistically significantly different risks of hospitalisation for selected ENMDs. Expected counts for 2007 were calculated using 2006 census populations and census 2011 for 2012. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT. * see text for clarification

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While maps of all CSDs showed 131x79mm (300 x 300 DPI)

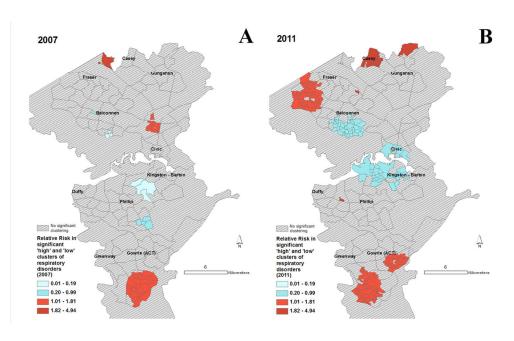


Fig 5: Spatial patterns of respiratory disease risk

Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with statistically significantly different risks of hospitalisation for respiratory diseases. Expected counts for 2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT

diseases (Figure 5) or were no 131x79mm (300 x 300 DPI)

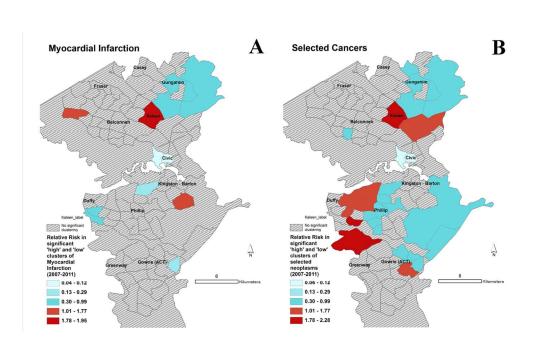


Fig 6: Spatial patterns of MI and cancer risk

Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT. BMJ Open: first published as 10.1136/bmjopen-2016-012548 on 8 December 2016. Downloaded from http://bmjopen.bmj.com/ on June 12, 2025 at Agence Bibliographique de I Enseignement Superieur (ABES) . Protected by copyright, including for uses related to text and data mining, Al training, and similar technologies.

problems with SaTScan is its p 131x79mm (300 x 300 DPI)

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Table S1.1: Summary of key individual level covariates in hospitalization data

Percent Female	53.55
Percent Married or in De Facto Relationship	48.74
Percent with Private insurance	87.96
Percent with hospital insurance	72.17
Median age	63 years

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		BMJ Open BMJ Open 2016	
	STI	ROBE 2007 (v4) Statement—Checklist of items that should be included in reports of cress-sectional studies 문 &	
Section/Topic	ltem #	Recommendation	Reported on page
Title and abstract	1	(a) Indicate the study's design with a commonly used term in the title or the abstract	2 Section 1
		(b) Provide in the abstract an informative and balanced summary of what was done and what was found	2 Section 1
Introduction		anen lateo	
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported to the Dot t	3
Objectives	3	State specific objectives, including any prespecified hypotheses	3
Methods		and	
Study design	4	Present key elements of study design early in the paper	4
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, b b - up, and data collection	4-7
Participants	6	(<i>a</i>) Give the eligibility criteria, and the sources and methods of selection of participants	4-7
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers diagnostic criteria, if	4-9
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe	4-9
Bias	9	Describe any efforts to address potential sources of bias	10-13
Study size	10	Explain how the study size was arrived at	NA
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which aboutings were chosen and why	4-9
Statistical methods	12	(a) Describe all statistical methods, including those used to control for confounding	10-13
		(b) Describe any methods used to examine subgroups and interactions	NA
		(c) Explain how missing data were addressed	5
			NA
		(d) If applicable, describe analytical methods taking account of sampling strategy Image: Comparison of the sampling strategy (e) Describe any sensitivity analyses Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the sampling strategy Image: Comparison of the samplin	2 Different models
Results			

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graphique

		ajopen-2016- BMJ Open BMJ Open	Page 3
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, exangined for eligibility,	4-8
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	NA
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information of magosures and potential confounders	4-8
		(b) Indicate number of participants with missing data for each variable of interest	4-8
Outcome data	15*	Report numbers of outcome events or summary measures	
Main results	16	(<i>a</i>) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision geg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	14-17
		interval). Make clear which confounders were adjusted for and why they were included (b) Report category boundaries when continuous variables were categorized 고급 효율	14-17
		(c) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful translating estimates of relative risk into absolute risk for a meaningful	NA
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyse	NA
Discussion			
Key results	18	Summarise key results with reference to study objectives	19
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	19-21
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	19-21
Generalisability	21	Discuss the generalisability (external validity) of the study results	19-21
Other information		ar to	
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	22

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in centrol studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicinemorg/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.s observatement.org.

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Is Walk Score® associated with Hospital Admissions from Chronic Diseases? Evidence from a Cross Sectional study in a High Socio- Economic Status Australian City State

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Primary Subject Heading :	Epidemiology
Secondary Subject Heading:	Cardiovascular medicine, Public health
Keywords:	Geographical Information Systems, Chronic Diseases, Spatial Analysis, Walkability, Built Environment and Health, Australia

SCHOLARONE[™] Manuscripts

Is Walk Score[®] associated with Hospital Admissions from Chronic Diseases? Evidence from a Cross Sectional study in a High Socio- Economic Status Australian City State

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Abstract

OBJECTIVES: To explore patterns of non-communicable diseases (NCDs) in the Australian Capital Territory (ACT).To ascertain the effect of the neighbourhood built environmental features and especially walkability on health outcomes, specifically for hospital admissions from NCDs.

DESIGN: A cross-sectional analysis of public hospital episode data (2007-2013)

SETTING: Hospitalisations from the ACT, Australia at very small geographic areas.

PARTICIPANTS: Secondary data on 75,290 unique hospital episodes representing 39,851 patients that were admitted to ACT Hospitals from 2007 to 2013. No restrictions on age, sex or ethnicity.

MAIN EXPOSURE MEASURES: Geographic Information System derived or compatible measures of General Practitioner access, neighbourhood Socio Economic Status, alcohol access, exposure to traffic

and WalkScore® walkability.

MAIN OUTCOME MEASURES: Hospitalisations of circulatory diseases, specific endocrine, nutritional and metabolic diseases, respiratory diseases and specific cancers.

RESULTS: Geographic clusters with significant high and low risks of NCDs were found that displayed an overall geographic pattern of high risk in the outlying suburbs of the territory. Significant relationships between neighbourhood walkability as measured by Walk Score® and the likelihood of hospitalisation with a primary diagnosis of Myocardial Infarction (heart attack) were found. A possible relationship was also found with the likelihood of being hospitalised with four major lifestyle related cancers.

CONCLUSIONS: Our research augments the growing literature underscoring the relationships between the built environment and health outcomes. In addition it supports the importance of walkable neighbourhoods, as measured by Walk Score[®], for improved health.

1 2 3 1 4 5	Strengths and limitations of this study
6 2 7 2	• This is one of the few studies that investigate the relationship between walkability and
8 3 9	hospitalisations from heart disease and specifically myocardial infarction while simultaneously
10 4 11	investigating other chronic conditions and built/social environment drivers of health.
12 5 13	• This is the first study to report a significant relationship between heart attacks and walkability
14 6 15 6	(measured using Walk Score®).
16 17 7	• While there have been many walkability studies in low SES and demographically mixed areas this
18 19 8	is one of the few to report significant results from a relatively egalitarian, well educated, wealthy
20 21 9	region.
22 23 10	• The cross sectional nature of this study makes it difficult to infer causal relationships.
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30 31 14	• The cross sectional nature of this study makes it difficult to infer causal relationships.
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28 Introduction

29 Background

Increasing rates of lifestyle-related non-communicable diseases (NCDs) such as cardiovascular disease and type 2 diabetes remain an area of public health concern in developed (and increasingly in developing) countries. In Australia, NCDs remain the predominant drivers of premature mortality and co-morbidity [1] .The Australian Capital Territory (ACT), is the wealthiestⁱ [2] and best educated state in Australia [3]. It has also been rated as one of the best places in the world to live by the Organisation for Economic Co-operation and Development [4], and has routinely been voted as the most liveable city in Australia [5]. In the annual "Australian Cities Liveability Survey" residents of Canberra have voted the city as being safe, affordable, having good employment and economic opportunities, having plenty of good schools/educational opportunities and an attractive natural environment with a wide range of opportunities for outdoor recreation activities [5]. In addition, there is a relative absence of heavy industry in ACT. Therefore, there is a general opinion that the ACT is an 'exceptional' city state in Australia with regard to its environment and planning. It follows therefore, that such a salubrious environment coupled with an educated population should encourage healthy lifestyle behaviours such as increased physical activity, which in turn should lead to significantly lower rates of lifestyle-related NCDs compared to the rest of Australia. Paradoxically, however, this expectation is not reflected in the ACTs burden of NCDs or lifestyle related risk factors relative to the rest of Australia. For example, adult prevalence of obesity/overweight in the ACT is 62.2% compared to an Australian average of 63.48%[6]. In addition rates of childhood obesity in the ACT are similar to those reported nationally. Furthermore, key environmental indices such as walkability in the ACT are not significantly different from the walkability in other major metropolitan cities in Australia [7]. While city level measures of walkability are of questionable value, our research, as outlined later in this paper, shows that at the very least there are significant variations in walkability within

53 the ACT, with the majority of suburbs being car dependent.

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Unlike many other cities, a high degree of government ownership and control over land has resulted in a unique pattern of suburb development in the ACT [8]. The planning has attempted to mimic a geographic "central place"[9] hierarchy with each suburb having its own suburb centre with shops and other destinations. Suburbs are nested within larger districts. The ACT comprises 8 populated districts. Each district has a central suburb, which is usually a very accessible, densely settled geographic central place with access to various local destinations including services, shops and other amenities. Some of these centres are also well served by public transport. Finally, in the centre of the ACT itself is the suburb of 'Civic', the central business district, with a very high degree of destination density. In spite of extensive planning, many suburb centres have over the years, been affected with shop, school and other destination closures [8] resulting in a reduction in the number of local amenities and reduced walkability. Thus, planned and unplanned variations in the cityscape imply that residents are exposed to a variety of physical environments which in turn may result in different health behaviours and resulting NCDs within the geographic boundaries of the ACT. Investigation of the spatial patterns of key NCDs *within* the ACT and their associations with the physical and social environmental features can help identify environments that lead to adverse health outcomes and highlight which design features of these environments are significantly associated with specific health outcomes. In addition to spatial variations in the built environment, an additional aspect that makes the ACT ideal for studying such relationships is the relatively high Socio Economic Status (SES) of the majority of its residents [2, 3] though there are pockets of poverty [10]. It has been repeatedly demonstrated, that if beneficial relationships do exist between the built environment and healthy behaviours (and consequent health outcomes), they are more likely to be found in high SES locales such as the ACT [11, 12], since the relationship between environment and behaviour is confounded by a negative perception of the environment in low SES individuals[13]. Therefore this research project had two aims: 1) To explore the spatial patterns of NCD-related hospital admissions in a relatively high SES Australian urban area - the ACT and 2) To investigate the built environmental correlates, adjusted for key

81 individual level factors.

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84 Methods

Conceptual Framework

We start with a theoretical basis of the well-known public health triad of environment, behaviours and health outcomes. Health outcomes are influenced by health behaviours, which in turn are associated with the environment. We summarize this in Figure 1. In Australia and elsewhere, a number of research papers have established the relationships between environment and behaviours (Link A – see figure 1) [14-18] or behaviours and health outcomes (Link B- see figure 1) [19, 20]. It logically follows that the environment is related to health outcomes through the individual lifestyle behavioural pathway. In addition, the built environment may directly influence health outcomes. For example, air pollution may be detrimental to respiratory and cardiovascular health [21], or perceptions on the environment may affect mental health [22]. However, research on this relationship (Link C-see figure 1) is limited, with most research, excepting a few [23, 24], focussing on outcomes related to sedentary health behaviours such as obesity [25, 26] and conditions directly related to obesity [27]. Our interest, therefore, was in investigating this relationship (Link C- figure 1), between aspects of the physical environment and the four major NCDs in the ACT: circulatory system diseases, specific cancers, Endocrine Nutritional and Metabolic Disorders (ENMDs) and respiratory disorders, using geocoded ACT hospitalisation data (from 2007 to 2013) and specific built environmental attributes. Note however, that Link C is mediated through multiple pathways, such as through health behaviours, and Link C represents any relationship between environmental exposures and the chronic conditions described above, irrespective of mediating pathway Fig 1: Framework of relationships between environment, behaviours and health outcomes **Investigating Relationships** To investigate relationships between the built environment and NCD-related hospital admissions, we

109 followed a combined exploratory-inferential approach. First, we asked "What are the spatial patterns of

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110 the four key chronic conditions in the ACT?" This is addressed through exploratory mapping using 111 spatial cluster analysis. Second, we investigated relationships between various individual and 112 environmental predictors such as neighbourhood walkability, traffic volume, and access to off-license 113 alcohol outlets and the key NCD-related hospital admissions in the ACT. In the next section, we explain 114 in detail the methods used to achieve this. The research was approved by the ACT Health Human 115 Research Ethics Committee (Ref.: ETH.11.14.310) on 8th December, 2014. 116 Data 117 118 **Hospital Data** 119 120 ACT Admitted Patients Data Collection (APDC) data were supplied by the ACT Health Directorate. This 121 consisted of 75,290 unique hospital episodes representing 39,851 patients admitted to all ACT public 122 hospitals between 1st January 2007 and 31st December 2013. Data were provided after ethics and other 123 data regulation requirements from the data custodian (Executive Director Performance Information, 124 ACT Government Health Directorate, Canberra) had been met. The data were deemed sufficiently 125 anonymous to not require individual patient consent. Public hospitals capture around 80% of all 126 hospitalisations" in Australia [28]. The patient hospital admission data had Australian Census - Australian 127 Bureau of Statistics (ABS) Mesh Block (30 to 60 dwellings), Statistical Areas Level 1 (SA1s) (200-800 128 people) and SA2 (3,000-25,000 people) geocodes attached to them, therefore no additional geocoding was 129 necessary. Each patient was geocoded to their place of residence. Geocoding completeness [29] varied 130 with geographical scale with 7,284 records missing at Mesh Block level, but only 949 missing at the SA2 131 level. A single hospital episode included a primary diagnosis and up to a hundred other diagnoses. 132 Primary diagnoses only have been used in the analyses considered here 133 134 Selection of NCDs 135 The Global Burden of Disease 2010 study [30] and the Australia profile derived from this [31] have 136 demonstrated unequivocally the dominance of NCDs in the burden of overall disease in Australia. In

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2010, nine out of the top ten risk factors, accounting for almost 50% of the total disease burden (in disability-adjusted life years), were lifestyle-related. The four broad NCD categories included in this study were chosen as they currently contribute the greatest burden in terms of health care resource cost in the ACT. While all hospitalisations for four ICD-10 codes: E, C, J and I, were provided, we divided the data into specific sub-codes, removing conditions with obvious genetic or familial drivers (i.e. not directly related to

lifestyle risk). Note that these ICD-10 codes could have been a primary or an additional diagnosis. Each

condition was analysed separately and with comorbidity. The subsets of ICD-10 codes used in our

analyses were:

A) Circulatory Diseases: all diseases of the circulatory system i.e. ICD 10 (100-I99) code T' (circulatory

system diseases or CSDs). However, we also created a data subset of hospital admissions with a primary

diagnosis for Myocardial Infarction (MI) and subsequent infarctions (ICD 10 codes I21 and I22

respectively). MI or heart attack represents a serious and sudden event generally requiring immediate

hospitalisation.

B) Cancers: We included cancers of the breast 'C50', colorectal cancers 'C18-C21', Endometrial Cancer

'C54.1' and lung cancers 'C33-C34'. These cancers have been associated with lifestyle risk factors [32].

C) Endocrine, Nutritional and Metabolic Diseases (ENMDs) - E10-E16 and E-66.

D) Diseases of the Respiratory system – J00-J99 i.e. all diseases of the respiratory system.

Table 1 describes the overall episodes of hospitalisation related to NCDs.

Table 1: Total hospitalisations for each non-communicable disease category by year^a

Year	Specific cancers	Respiratory system	CSD	МІ	ENMD	Any of the four major NCDs
	eaneers					
2007	573	3381	4992	369	1673	8051
2008	661	3762	5314	415	1618	8796
2009	709	3639	5492	528	1411	8913
2010	680	3646	5126	516	1075	8563
2011	716	4203	5379	530	793 ⁺	9316
2012	714	4405	5458	543	1498	9453
2013	704	4273	5391	491	2041	9234

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158 159 160	^a Some hospitalisations were for multiple conditions, thus totals with any of the four major NCDs were less than the sum of single NCDs; CSD-circulatory system disease, MI–myocardial infarction; ENMD–endocrine, nutritional and metabolic diseases; NCD–non-communicable disease; + The numbers of ENMDs in 2011 are anomalously low, the reason for this is not known.
161	
162	Of these conditions CSDs and ENMDs are known to be associated with a sedentary lifestyle, as is
163	obesity, colorectal and endometrial cancer [32]. Lung cancers and respiratory diseases are driven to a great
164	extent by smoking and air quality.
165 166	For statistical modelling and analysis, we used all hospital admission episodes (2007-2013), but for spatial
167	mapping we further sub-divided the hospital data to the years 2007 and 2011 because these link to the
168	national censuses (2006 and 2011) with available reference population data. The individual level covariates
169	that were included in the hospital data were gender, age (years), marital status, private insurance and
170	hospital insurance. The raw data included other variables that were not relevant to this study such as
171	length of hospital stay, medical procedures performed and days (if any) in the psychiatric ward. The last
172	two variables may serve as proxy measures of SES. The covariates are summarized in Appendix S1 Table
173	S1.1.
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	Population Data In addition to the above data, population data were required for mapping rates of hospital admission. The
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177 178	In addition to the above data, population data were required for mapping rates of hospital admission. The
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177 178 179 180	In addition to the above data, population data were required for mapping rates of hospital admission. The smallest geography at which Australian demographic data (for example age, gender, SES) are released is the Statistical Area 1 (with an average of 500 people). SA1 is therefore a relatively small geographic area at
177 178 179 180 181	In addition to the above data, population data were required for mapping rates of hospital admission. The smallest geography at which Australian demographic data (for example age, gender, SES) are released is the Statistical Area 1 (with an average of 500 people). SA1 is therefore a relatively small geographic area at which NCD-related hospital admission rates could be mapped. However, there were relatively smaller
177 178 179 180 181 182	In addition to the above data, population data were required for mapping rates of hospital admission. The smallest geography at which Australian demographic data (for example age, gender, SES) are released is the Statistical Area 1 (with an average of 500 people). SA1 is therefore a relatively small geographic area at which NCD-related hospital admission rates could be mapped. However, there were relatively smaller numbers of neoplasm and MI cases (Table 1) hence these conditions required a larger geography, - the
177 178 179 180 181 182 183	In addition to the above data, population data were required for mapping rates of hospital admission. The smallest geography at which Australian demographic data (for example age, gender, SES) are released is the Statistical Area 1 (with an average of 500 people). SA1 is therefore a relatively small geographic area at which NCD-related hospital admission rates could be mapped. However, there were relatively smaller numbers of neoplasm and MI cases (Table 1) hence these conditions required a larger geography, - the SA2 for mapping because rates based on small numbers of expected cases are unstable and have large
177 178 179 180 181 182 183 184	In addition to the above data, population data were required for mapping rates of hospital admission. The smallest geography at which Australian demographic data (for example age, gender, SES) are released is the Statistical Area 1 (with an average of 500 people). SA1 is therefore a relatively small geographic area at which NCD-related hospital admission rates could be mapped. However, there were relatively smaller numbers of neoplasm and MI cases (Table 1) hence these conditions required a larger geography, - the SA2 for mapping because rates based on small numbers of expected cases are unstable and have large confidence intervals. In this study the term suburb is used to define the spatial boundary defined by the
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188	
189	Australian census output geographies changed significantly between 2006 and 2011. While, there are
190	minimal differences between 2011 SA2 geographies and their 2006 counterpart Statistical Local Areas
191	(SLAs) in the ACT [33], there was significant spatial mismatch between 2011 SA1s and their 2006
192	counterpart in the census hierarchy- Collection Districts(CDs). Thus, when mapping by SA1s or CDs
193	(ENMDs, respiratory diseases and CSDs), we show separate maps for 2006 and 2011. Age specific 2011
194	population counts at SA1s and 2006 counts at CDs were obtained from the ABS. For SA2 level maps of
195	neoplasms and MI, counts of expected numbers of cases for the years 2007-2011 were required. Age
196	specific 2011 population counts and 2006 population counts were obtained at SA2s/SLAs. To obtain the
197	age distribution for the intermediate years (2007-2011) at SA2s, we linearly interpolated the numbers in
198	each SA2/age group between 2006-2011. This generated the fraction of people in each age group in a
199	given year in a SA2. We then used an indirect age standardization technique to calculate annual expected
200	numbers of cases of an NCD using the annual age distributed ACT population as the standard population
201	[34]. Expected annual numbers were also calculated for the CD, SA1 and SA2 data. We used 2006
202	expected counts when mapping 2007 hospitalisation data since 2007 SA1 or CD population counts were
203	not available.
204	

206 Environmental Data

As summarised in Figure 1, we wanted to investigate relationships between various built environmental attributes and health events ((hospital admissions). A number of environmental covariates were collected, collated and/or created in-house by the authors. Our choices of environmental drivers were informed by previous research but also constrained by the available data. For example, we did not have geocoded data for food outlets so could not explore any relationships between hospital admissions and the food environment. The environmental indices that were available are described below: 1. Walkability: Walking is the most prevalent form of physical activity in the population [35, 36]. The degree of neighbourhood walkability predicts the degree of walking[37]. We measured the physical activity environment through suburb level walkability. While other

Page	11	of	39
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aspects of the physical activity environment such as centres are also important, the walking network rema environmental attributes for overall physical activity walkability produced by a United States based comp been utilized in a number of public health studies in context, it has been found to have strong relationshi study [14], though relationships with health outcome Walk Score® is a composite measure of destination of	hains one of the most important built 7 [13]. Walk Score [®] is a measure of pany that has been validated [37] and has 1 the United States. In the Australian ips with walking for transport in a recent
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context, it has been found to have strong relationshi study [14], though relationships with health outcome	ips with walking for transport in a recent
study [14], though relationships with health outcome	
	es have not previously been found [23] .
Walk Score [®] is a composite measure of destination of	
	density. The scores are normalized to a 0
to 100 scale, with 0 being the lowest walkability and	100 being the highest. A five scale
categorization is used; "Walkers Paradise" (Walk Sco	ore® 90-100), "Very Walkable" (70-89),
"Somewhat walkable" (50 to 69), "Car-dependent" ((25 to 49)" and "Car Dependent" (0-24)
by the developers of Walk Score [®] [38] and these cate	regories have been used by other
researchers [16]. Walk Scores® for ACT suburbs/S.	SA2s were obtained from the Walk
Score [®] website [38]. A map of Walk Scores [®] at ACT	Γ suburbs is provided in Figure 2.
Fig 2: Map of five categories of Walk Score® by AC	T suburbs
The five categories are "Walkers Paradise" (Walk Score®	
"Somewhat walkable" (50 to 69), "Car-dependent" (25 to	to 49)" and "Car Dependent" (0-24)
2. Access to General Practitioners: access to primary ca	are is an important predictor of
admittance into tertiary facilities [39, 40]. Access to C	General Practitioners (GPs) is related to
better health management and lesser use of hospital	services [39, 41]. We created an access
measure by drawing a circular buffer around the Mes	esh Blocks of the patients in the
hospitalisation data. The circular buffers around the	Mesh Blocks adaptively grew to
	l of 1000 people were included in the
different sizes, with each buffer growing until a total	
different sizes, with each buffer growing until a total circle. The numbers of GP clinics in the buffer circle	es were then summed to provide an
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circle. The numbers of GP clinics in the buffer circle	-
 by the developers of Walk Score® [38] and these cate researchers [16]. Walk Scores® for ACT suburbs/S. Score® website [38]. A map of Walk Scores® at ACT Fig 2: Map of five categories of Walk Score® by AC. The five categories are "Walkers Paradise" (Walk Score® "Somewhat walkable" (50 to 69), "Car-dependent" (25 to 2000). 2. Access to General Practitioners: access to primary catedonittance into tertiary facilities [39, 40]. Access to General Practicular buffer around the Messer access by drawing a circular buffer around the Messer access ac	regories have been used by other SA2s were obtained from the Walk I' suburbs is provided in Figure 2. T suburbs 90-100), "Very Walkable" (70-89), to 49)" and "Car Dependent" (0-24) eare is an important predictor of General Practitioners (GPs) is related to I services [39, 41]. We created an access esh Blocks of the patients in the Mesh Blocks adaptively grew to

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 data for 2010 were provided by the ACT Medicare Local, while underlying 2011 census population data were obtained from the ABS. Neighbourhood SES: is a well-established marker of social environment including crime and social cohesion and a mature literature supports the relationship between neighbourhood SES and a range of health outcomes [42]. The Socio-Economic Indexes for Areas (SEIFA) are indices of area level of Socio-Economic Status in Australia developed by the ABS. The Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD) is one such index that measures both advantage and disadvantage. The index was created by incorporating a number of measures including percent unemployed, car ownership and percent disabled. SA1 level IRSAD scores for 2011, the finest resolution at which they are available were incorporated into these analyses. Alcohol outlets: along with the food environment alcohol outlets are powerful predictors of lifestyle-related health outcomes [43]. While the food environment is best represented by summary measures of access to a range of food outlets, we did not have access to an integrated, clean, geocoded dataset of food outlet locations in the ACT for this study (see Discussion). Easy access to alcohol has been related to a number of negative health and social outcomes [44, 45], and we have used a measure of alcohol access in our analyses. A list of all licensed off-license liquor outlets was obtained from the ACT Department of Regulatory Services [46] and geocoded to SA1 level. Off-license outlets are licensed to sell alcohol, but alcohol cannot be consumed within premises, examples of which include supermarkets and bottle shops. The road network distance from each residential parcel within each SA1 to the nearest off license liquor establishment was calculated. The mean distance for all residential parcels per SA1 was then derived. Off license outlets were included if they were within the same ACT defined district as the SA1 of interest.

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272	5.	Road Traffic Exposure: The presence of road traffic can act as an impediment to physical
273		activity in a neighbourhood environment [47]. Road traffic exposure was based on a ratio of
274		road hierarchy (as a proxy for traffic volume) by length of road segments within an SA1.
275		Methods for this have been published previously [47].
276		

278 Analysis

Spatial patterning of hospital admissions related to NCDs were explored using a cluster detection tool,
the Spatial Scan Statistic [48]. Monte Carlo regression was then employed to investigate relationships
between NCD-related hospitalisations and built environmental factors.[29, 49]. Finally, a negative
binominal was also employed to test the relationship between NCDs and built environmental factors.

284 Exploratory Spatial Scan Statistic

Exploratory methods allow us to generate hypotheses about relationships (Link C, Figure 1) by visually correlating significant spatial patterns of NCD-related hospital admissions with spatial patterns of environmental variables. We used the well validated and robust Spatial Scan Statistic to investigate significant spatial patterns [48, 50, 51]. This method asks "What area or what combination of areas is most likely to have a statistically significantly 'high' or a significantly 'low' risk relative to areas outside the combination of areas?" This would be framed as a "cluster detection problem" in the spatial epidemiology literature [48]. The Spatial Scan Statistic was implemented using the SaTScan software. This method implements a single maximum likelihood based hypothesis test over geographic space to identify the regions where the

distribution of cases relative to controls/population (or the expected number of cases) is most likely to be

- 296 consistent with a significant excess risk. To implement this, SaTScan identified candidate clusters, which
- 297 were circles of increasing radii, bound by a maximum population threshold radius (set here to 5% of the

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298 population), centred on pre-specified locations such as SA1 centroids. The size of the cluster is

299 sometimes sensitive to the threshold radius [52]. The 5% threshold represents around a few hundred

300 expected cases of most NCDs, and is sensitive enough to delineate small clusters, an early goal in our data

301 exploration and analysis.

302 Over many candidate clusters SaTScan maximizes the likelihood ratio, given by

303 LLR=O*ln(O/E)+O*ln((n-O)/(n-E))

304 Where, LLR represents the logarithm of the likelihood ratio, O are observed cases, E are expected cases, 305 and n is the total number of cases in the entire region (ACT). The likelihood formula assumes that NCD 306 cases are distributed as a Poisson random variable and the likelihood ratio is compared to simulated 307 likelihood ratios generated from 999 Monte Carlo randomizations of the data to assess statistical 308 significance. The area that has the highest likelihood value (or the lowest p value) is the primary cluster. If 309 both low and high risk clusters are searched for then the most likely (high and low) clusters will be 310 identified and published by the software. Secondary or less likely clusters may also be reported. In our 311 analyses we restricted our results to primary or secondary clusters with a significant p value. Relative risks 312 at the significant clusters were reported as: (risk inside the cluster)/(risk outside the cluster.) 313 SaTScan analyses were implemented for CSDs and respiratory diseases at the SA1 scale for 2011 and CD 314 scale for 2007. Because of an unexplained anomalously low number of hospitalisations for ENMDs in 315 2011 (Table 1), we scanned 2012 SA1 and 2007 CD ENMD data. Due to lower event rates, MI and 316 selected cancers were analysed at the SA2 scale for the entire aggregated 2007-2011 period. Thus, SA2 317 level observed and expected numbers were summed for the entire 5 year period 2007-2011. Results were 318 mapped using ArcGIS 10.1. 319 Associations between built environment factors and hospital admission 320 321 rates 322

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323	We used two different models to investigate the relationships between the various NCD-related hospital
324	events and built environment characteristics. The hospital admission data were complex, with multiple
325	cross classifications and nesting. For example, each person in the data could be hospitalised multiple
326	times (nesting of hospitalisation episodes within people), people were nested in geographic
327	neighbourhoods such as suburbs, and the temporal nature of the data, implies likely temporal trends and
328	seasonal patterns. In addition, the distributions of a number of predictors such as suburb level Walk
329	Score® or GP density were not normal, which would render traditional linear models unusable, or require
330	complex statistical transformations and/or models. To overcome this problem we first modelled
331	relationships using a robust method: Monte Carlo logistic regression [29, 49]. The approach was as
332	follows:
333	1. Randomly sample 50% of the data
334	2. Fit logistic regressions (or any other model to be tested) to estimate best explanatory model, store
335	parameter estimates: intercept and slope values
336	3. Repeat steps 1 and 2, N times (In our simulations N=1000)
337	4. Calculate mean and 95% confidence intervals for estimated model parameters from stored values in
338	step 2.
339	We utilized logistic regressions as our explanatory model, with each hospitalisation event with a primary
340	diagnosis of respiratory diseases as the control condition. The dependent variable was a hospitalisation
340	
	event (1/0) with a primary diagnosis of each of the NCDs described in the data section, - cancers, CSDs,
342	MI, ENMDs and comorbids being coded as 1. Separate models were run for each of MI, CSDs, specific
343	neoplasms, ENMDs and comorbids. Respiratory diseases were chosen as the control condition, or coded
344	as 0, because the drivers of respiratory disorders, with the exception of smoking, generally differ from the
345	environmental drivers of the other three conditions. (While ideally we would have liked to use all
346	hospitalisations as controls, these data were not available at the time of analysis). When modelling
347	neoplasms, since lung cancers have somewhat different environmental drivers than the remaining cancers,
348	we ran the model with and without lung cancer. We also attempted to model hospitalisations with
349	comorbid CSDs, specific neoplasms, ENMDs and respiratory diseases conditions by coding
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logged traffic exposure.

hospitalisation with more than one condition as 1, and the rest 0. The independent variables in these models were: sex, age, marital status, payment with private insurance (yes/no) of the person hospitalised. All these covariates, with private insurance as a marker of SES are known to be associated with chronic conditions [53]. In addition ecological level independent variables (described in the data section) include the hospitalised person's access to GPs, neighbourhood walk score, IRSAD score, access to alcohol and

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We also report McFadden's pseudo-R² for the Monte Carlo regression analyses. We understand that the use of pseudo- R^2 is controversial [54], and publish these values for researchers who prefer to see them reported. These values were not used for model selection or for any other judgement on model quality.

Finally, for NCDs with significant environmental correlates in the Monte Carlo model we also modelled the total number of hospitalisation events of a given condition in a given suburb as a function of counts of different predictors. The models can be written as:

 $Y_j \sim \text{Negbin}(\mu_j, \kappa)$

 $\mu_{i} = e^{(\beta 0 + \sum_{k} \beta_{k} x_{jk})}$

Where Y_i is the total count of a given condition in suburb j and x_{ik} is the count of the k'th predictor in the j'th suburb, for example, - the total number of insured patient hospitalisations in a suburb or total number of female patient hospitalisations in a suburb. Y_i was considered to be negative binomially distributed with mean μ_i and variance κ . A negative binomial model was used after it was found that the data were overdispersed, rendering a Poisson model unsuitable. The mean μ_i or suburb level count of a given outcome was modelled as an exponential function of an intercept term β_0 and a slopes term β_k . These models require aggregate counts or summaries at the suburb level, and variables were recoded to satisfy this requirement. Thus, for example, discrete variables such as the marital status of a hospitalised person (1/0) translated to the total number of hospitalisations of married people in a given suburb. Continuous variables were similarly recoded, such as the number of hospitalisations of people in the topmost quartile of traffic exposure, number of hospitalisations of people in lowest decile of IRSAD,

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number of hospitalisations of people with good GP Access and so on. People with a GP density of 1 ormore in their immediate buffer neighbourhood were considered to have good access.

We were interested in modelling counts of a hospitalisation outcome (e.g. heart attack hospitalizations) in a small area as a function of counts of the characteristics of the hospitalised population in the negative binomial models. Note that the population size of a suburb does not necessarily predict the number of hospitalisations which is a function of a number of neighbourhood compositional characteristics such as age, sex and SES. Counts of hospitalisations that capture these characteristics were included in the model. While modelling heart attacks as a fraction of all hospitalisations could be an alternative model, the results of the count negative binomial model, as described in the next section converge with the results from the logistic MCMC model, underscoring the strength of our analyses. The models were implemented using R and Stata.

Results

Figures 3 to 6 display the results of the Spatial Scan Statistic analyses. We report all significant clusters of both 'high' and 'low' risk. Reporting all significant clusters instead of the "most likely" cluster has been shown to enhance exploratory analyses [52, 55]. The scan results displayed a general trend of higher risk of hospital admissions in the outer suburbs and lower risk in the inner suburbs. Thus, the suburbs of Civic and Kingston-Barton either had significantly lower risk of CSDs (Figure 3), MI (Figure 6) and respiratory diseases (Figure 5) or were not significantly different clusters (Figures 3-6). While maps of all CSDs showed some random variation from 2007 to 2011, sections of West Belconnen around Fraser and areas south of Gowrie; and north of Gunghalin showed consistent high risk of CSDs (Figure 3). Some of these areas also showed consistent high risks of ENM diseases (Figure 4).

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- 397 Fig 3: Spatial patterns of CSD risk

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398 Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with 399 statistically significantly different risks of hospitalisation for all CSDs. Expected counts for 2007 were 400 calculated using 2006 census populations. Relative risk for a given contiguous cluster was calculated 401 relative to the risk in the rest of the ACT.

402

403 Fig 4: Spatial patterns of ENMD risk 404

405 Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2012* with 406 statistically significantly different risks of hospitalisation for selected ENMDs. Expected counts for 2007 407 were calculated using 2006 census populations and census 2011 for 2012. Relative risk for a given 408 contiguous cluster was calculated relative to the risk in the rest of the ACT. * see text for clarification 409

410 Fig 5: Spatial patterns of respiratory disease risk

411 Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with 412 statistically significantly different risks of hospitalisation for respiratory diseases. Expected counts for 413 2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was

- 414 calculated relative to the risk in the rest of the ACT
- 415
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- 417
- 418 The spatial patterns of MI and cancer risk (Figure 5) did not show a consistent pattern though we can see
- 419 that highly walkable suburbs such as Civic, Kingston-Barton and Belconnen were either low risk (Relative
- 420 Risk/RR <0.13) clusters or were non-significant clusters. One of the recognized problems with SaTScan
- 421 is its propensity at larger geographic scales to detect large low risk clusters in rural, sparsely populated
- 422 areas. Thus, areas North East of Gungahlin, and some areas south east of Kingston-Barton appear as low
- 423 risk clusters, which in reality have very few residents (Figure 6).
- 424

425

426 Fig 6: Spatial patterns of MI and cancer risk 427

428 Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation 429 for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to 430 the risk in the rest of the ACT. 431

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The results of Monte Carlo logistic regressions showed significant relationships between suburb level Walk Score® and the risk of Myocardial Infarction (Table 2). Specifically there was a 4% 1.04 (95% CI: 1.01, 1.07) increased odds of being hospitalised for a heart attack from living in a neighbourhood that is not a "Walker's Paradise". Similarly, there was a significant progressively increasing risk of being hospitalised with cancer when living in increasingly less walkable suburbs. When lung cancers were removed from the set of four cancers (not shown), the effect sizes remained the same, but the confidence intervals widened, becoming marginally non-significant. This probably indicates that the relationship with neoplasms are likely valid, but the regressions are underpowered due to small numbers. A high pseudo R² of around 95% in the MI model was reported underscoring our earlier comment that these values should be interpreted with care.

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Table 2: Summary of robust Monte Carlo logistic regression derived Odds Ratios with 95% Confidence Intervals for each NCD hospitalisation outcome*

Predictor	CSD	MI	ENMD	Selected Neoplasms	More than one comorbid NCD
Individual Level Variables					
(Intercept)	1.09 (0.98 , 1.21)	0.99 (0.95 , 1.02)	1.14 (1.02 , 1.27)	0.85 (0.81 , 0.9)	0.02 (0.00, 0.13)
Female	0.95 (0.94 , 0.96)	0.97 (0.97 , 0.98)	0.95 (0.94 , 0.96)	1.09 (1.08 , 1.10)	0.86 (0.83 , 0.90)
Age in years	1.01 (1.01 , 1.01)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.04 (1.04 , 1.04)
Married	1.11 (1.1 , 1.12)	1.02 (1.01 , 1.02)	1.04 (1.03 , 1.05)	1.06 (1.05 , 1.07)	0.93 (0.89 , 0.98)
Paid with private insurance	0.99 (0.98 , 1.01)	1.06 (1.05 , 1.07)	0.99 (0.97 , 1.01)	1.08 (1.07 , 1.10)	0.98 (0.91 , 1.06)
Has hospital insurance	1.02 (1.01 , 1.03)	0.98 (0.97 , 0.99)	0.99 (0.98 , 1.01)	0.97 (0.96 , 0.98)	0.90 (0.84 , 0.95)
Ecological Variables					
Access to GP clinic	1.00 (1.00 , 1.01)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	0.99 (0.97 , 1.01)
Walk Score®					
Reference: Walker's paradise (Score 90 to 100)	X				
Very walkable (Score 70 to 89) or Somewhat walkable (Score 50 to 69)	1.02 (0.92 , 1.13)	1.04 (1.01 , 1.07)	1.07 (0.97 , 1.19)	1.06 (1.01 , 1.12)	1.87 (0.37 , 9.4)
Car-dependent (Score 25 to 49) or Car dependent (Score 0 to 24)	1.03 (0.93 , 1.14)	1.04 (1.01 , 1.07)	1.09 (0.98 , 1.2)	1.07 (1.01 , 1.12)	2.02 (0.04 , 10.24)
IRSAD score	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)	1.00 (1.00 , 1.00)
Mean distance to off-license alcohol outlet Log traffic exposure	1.00 (0.99 , 1.01) 1.00 (1.00 , 1.00)	1.00 (0.99 , 1.01) 1.00 (1.00 , 1.00)	1.00 (0.99 , 1.01) 1.00 (1.00 , 1 .00)	1.00(0.99 , 1.01) 1.00 (1.00 , 1.00)	0.92 (0.88, 0.96) 1.00 (1.00, 1.00)
Pseudo R ^{2 a}	16.83	95.5	3.54	22.3	10.16

* Significant effects in bold. Significance levels were not computed for Monte Carlo estimates; X Walker's Paradise is the reference category while the two car dependent and two walkable categories are aggregated,^a Pseudo R² is a measure of the amount of variation explained by the model; CI-95% confidence interval; NCD-non-communicable diseases; CSD-circulatory system diseases; MI- myocardial infarction; ENMD-endocrine, nutritional and metabolic diseases; GP-General Practice, IRSAD-Index of Relative Socioeconomic Advantage and Disadvantage; Total number of hospitalisation events: N=75,290

The relationships were supported by the negative binomial model (Table 3). For example there are 4% less hospitalisations with myocardial infractions from neighbourhoods that are a walker's paradise relative to car dependent neighbourhoods. Somewhat counter-intuitive, relationships with hospital admissions from neoplasms were found, where those living in a neighborhood with more hospitalisations of low SES people or having less access to GPs decreased the likelihood of a neoplasm related hospitalisation which may suggest the potential for missed diagnoses. Being female was protective for circulatory disease, myocardial infarction, ENMD or hospitalisation with more than one condition but was a risk factor for selected neoplasms (Tables 2). Being married (or in a de-facto relationship) increased the risk of being hospitalised with any condition but decreased the risk of being hospitalised with multiple conditions (Tables 2). Results from the ecological model (Table 3) also support the findings from the Monte Carlo model. In Australia, while public hospital services are free, patients may have the choice of accessing private services for a fee, usually paid through insurance. Paying with private insurance was positively associated with MI hospitalisation or hospitalisation with selected neoplasms. Overall, the results of the regressions agreed with results of exploratory mapping - that is, the outlying low walkability suburbs have higher rates of key NCD-related hospital admission.

Table 3: Summary of rate ratios (CI)^a

Number of hospitalisations of :	МІ	Selected Neoplasms
Females	1.0005 (0.9978 , 1.0032)	1.0007 (0.9964 , 1.005)
Married people	1.0032 (1.0016 <i>,</i> 1.0049)**	1.0036 (1.0004 , 1.0068)+
Paid with private health insurance	1.0032 (0.9976 , 1.0087)	1.0047 (0.9953 , 1.0141)
People with with hospital insurance	0.9958 (0.9924 , 0.9992)*	0.9952 (0.9891, 1.0014)
People within 1 km distance to off-license alcohol outlets	0.9999 (0.9995 , 1.0003)	1.0001 (0.9992 , 1.0009)
People 44 and younger	0.9980 (0.9927 , 1.0033)	0.9829 (0.9691 , 0.9971)+
People 45 to 64	0.9980 (0.9923 , 1.0038)	0.9885 (0.9738 , 1.0034)
People 65 and over	0.9997 (0.9943 , 1.0050)	0.9856 (0.9715 , 0.9999)
People with good GP Access	1.0020 (0.9963 , 1.0077)	1.0172 (1.0033 , 1.0313)*
People living in suburbs that are a "Walker's Paradise"	0.9545 (0.9166 , 0.9782)*	0.9048 (0.7944 , 0.9583)*
People in "Very Walkable" or "Somewhat Walkable" suburbs	0.9999 (0.9997 , 1.0002)	1.0002 (0.9997 , 1.0008)
People in lowest decile of IRSAD	1.0000 (0.9994 , 1.0007)	0.9981 (0.9965 , 0.9996)*
People in topmost quartile of traffic exposure	0.9999 (0.9995 , 1.0003)	0.9995 (0.9986 , 1.0004)

CI-95% confidence interval; MI-myocardial infarction; GP-General Practice ;IRSAD-Index of Relative Socioeconomic Advantage and Disadvantage; Number of suburbs=90

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423 Discussion

424	We found that Walk Score® was significantly associated with hospital admission for MI. The spatial
425	patterns of MI admission rates and Walk Score® supported this finding. Thus, individuals residing in a
426	neighbourhood considered a "Walker's Paradise" (e.g. Civic) have significantly lower risks of admission
427	for MI after adjustment for age, gender, marital status and insurance status. A similar relationship existed
428	with certain neoplasms though further investigation is required to support this finding. The highest risks
429	of neoplasms and MI admission rates were found in Kambah (Walk Score®: 28) and Kaleen (Walk
430	Score®: 39) which were classified as 'Car Dependent' by Walk Score®. While a number of studies have
431	shown that Walk Score® is related to walking for recreation and transportation [14-16, 37] ours is one of
432	the few studies [23, 24] that showed a significant relationship between Walk Score® and hospital
433	admissions.
42.4	
434	Our analyses utilized suburb level Walk Scores [®] . It is known that there are significant differences in
435	walkability within suburbs, and therefore individual residential level Walk Scores [®] could capture more of
436	the variation in walkability in the ACT, and perhaps help in obtaining more robust estimates of the
437	relationships between key NCD-related hospital admission and walkability. Walk Score® itself, has been
438	criticized by some researchers as a measure of walkability though some of these criticisms, - such as the
439	use of "as the crow flies" distance have been rectified in the newer versions of Walk Score®, which we
440	have used [38]. Another shortcoming with the Walk Score® and other environmental data used in these
441	analyses is that they are from a single time point over the analysis period. While theoretically temporal
442	synchronisation between the environmental data and the health data is ideal, accessing archived spatial
443	datasets for different time periods of interest was not possible in a reasonable timeframe for this study.
444	Our data are from public hospital data, and we did not have access to private hospital data. While there is
445	a possibility that this may cause biases, public hospitalisations cover the majority of hospitalisations in the
446	ACT, and therefore are mostly representative of hospitalisations in this population [28]. Nevertheless, it is
447	possible that there are suburb level (or smaller area) variations in the proportion of private hospital
448	admissions relative to public hospital admissions. This may cause biases the extent of which are not

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known. Some of the areas with consistent low risk, such as Civic and Kingston-Barton (at the centre of the ACT) are areas with high residential density, easy access to shops and public transport. These areas also tend to draw a higher proportion of individuals who are younger and mobile, and are less likely to be hospitalised for any condition whatsoever. Since our regression models do not incorporate underlying population data, it is possible that variations in area level populations may affect our analyses. Nevertheless, exploratory cluster mapping *does* incorporate underlying population and we note that areas such as Civic, Phillip, Kingston-Barton were generally low risk clusters. Therefore the relationships are unlikely to be biased by population heterogeneity in hospitalisation rates. A recent similar study from Australia found no significant association between Walk Score® and the likelihood of Ischemic Heart Disease [23]. There could be multiple reasons for this, including the fact that the Walk Score[®] at geographic centroids of SLAs were used to summarize the Walk Score[®] in a given SLA. Since there is considerable variation of Walk Score[®] within an SLA, a geography much larger in size than SA2s in the aforesaid study, using centroid Walk Scores® may not be appropriate. In contrast we used an SA2/Suburb level Walk Score[®], which represents the average Walk Score[®] at the suburb level. Another reason as to why significant associations were not found in the study [23] could be the outcome investigated, - Ischaemic Heart Disease (IHD). This condition, like CSD, may remain undiagnosed in the population resulting in a hospitalisation dataset that is not representative of the true patterns of the condition in the population. MI, which is a severe acute outcome of undiagnosed IHD or CSD, is less likely to suffer from diagnostic bias. To our knowledge, at least one other study, in this case reporting results from the United States, has reported an association between mixed land use, better access to fitness facilities and a lower risk of coronary heart disease in low income women [24]. The local government area of ACT is high SES and relatively egalitarian being at the middle of the income inequality league relative to other local governments in Australia [56]. Car ownership in the ACT (603 per 1000 people) is well above the Australian average (568 per thousand) with only two states, Victoria and South Australia having higher ownership rates. In addition, public and active transport modes of travel to work are less popular in the ACT compared to other capital cities [57]. The combination of high SES, low walkability and high car ownership is known to discourage walking (recreational or transportation walking) [11, 12], which in turn may influence the risk of heart disease or cancer, as demonstrated in this

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study. It is possible that cars may enable informed individuals to shop for healthy foods, but the food environment beyond alcohol is not explored in this study. Incorporating the food environment in our analyses is an area of future work. Further work will include additional environmental measures (for example, air quality and crime will be included in the next phase), further refinement of indices (for example, mix of food outlets, nutritional quality of food available), closer analysis of the metric and distributional properties of each measure and better quality data on individual behaviours. In addition, future research should assess whether the present findings are replicated in similar, as well as in different, populations and settings.

This study utilizes an ecological cross sectional design which may generate bias. In addition patients could have a condition and not be hospitalised (e.g. death from MI before hospitalisation). Cancer registries could supply better quality and more comprehensive data than hospitalisation from neoplasms. Another limitation of our study is that we used respiratory disorders as our control condition in the regressions. This is because the drivers of respiratory conditions are generally different from the drivers of heart attacks, ENMDs etc. While our data, which were limited to the four conditions, constrained the analyses to this specific control, future analyses will attempt to incorporate all hospitalisations as control condition. We showed that there are relationships between walkability as measured by Walk Score and key NCDs providing support of the logical link between environment, behaviours and health outcomes (Figure 1: Link C). Nevertheless, we remain interested in investigating Link A, the relationship between environment and behaviours. Since 2013 data on life-style risk behaviours at the suburb level such as smoking/alcohol and BMI have become available through the ACT Adult health survey. Incorporation of these data into further analyses remains an area of future exploration. Furthermore, if individual level address information of the survey respondents were available, this would allow a more precise and accurate investigation of the effects of the built environment on lifestyle risk behaviours and NCDs.

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504	Our analyses form a unique and systematic investigation into the effect of built environment and
505	consequent NCD-related hospital admissions. This research highlights the significant role that walkability,
506	plays in health and in use of health care resources i.e. hospitals. While this research could have significant
507	bearings on local policymaking, it also captures a niche in the broader built environment and health
508	literature with its investigation of relationships between the built environment and health outcomes.
509	
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514	research project. Spatial data were sourced from a variety of ACT Government Directorates (including
515	Environment and Planning, Territory and Municipal Services and Justice and Community Safety) and we
516	are very grateful for Directorate staff assistance with regards to data access and technical advice which
517	made this research project possible.
518	The opinions expressed in this paper are those of the authors and not those of the funding body. The
519	funding body played no part in the design of the study, in the analyses and the interpretation of findings,
520	and in the decision to submit the manuscript as a publication.
521 522	Supporting Information
523	Appendix S1: Summary of key individual level covariates in hospitalisation data
524	
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529	

Competing Interests None declared Contributions SM, VL and TC implemented the data cleaning, statistical analyses and the writing. RD, HP and BC provided analytical oversight, reviewed the manuscript and helped with the writing. Data Sharing Statement The hospital data were provided after ethics and other data regulation requirements from the data custodian at HealthInfo@act.gov.au, Anyone with the appropriate ethics clearances can request the data tethics statement The research was approved by the ACT Health Human Research Ethics Committee (Ref.: ETH.11.14.310) on 8th December, 2014.
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- ¹ Median Household income/week in 2011-12 was AUD 2,124 compared to a national average of AUD 1,612
- u. governme. blish data repor. ⁱⁱ This is a national statistic. The ACT government does not collect and/or publish private hospitalisation data, but it is unlikely to differ significantly, since states that do publish data report similar fractions of public and private hospitalisations.

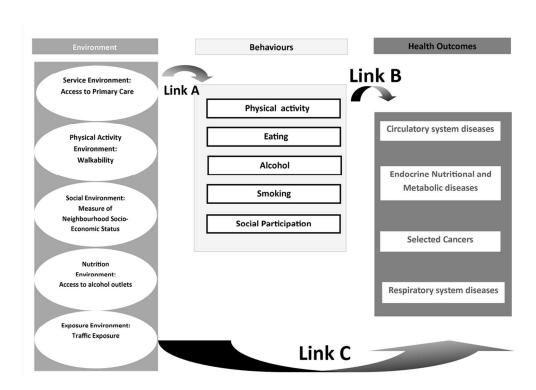


Fig 1: Framework of relationships between environment, behaviours and health outcomes

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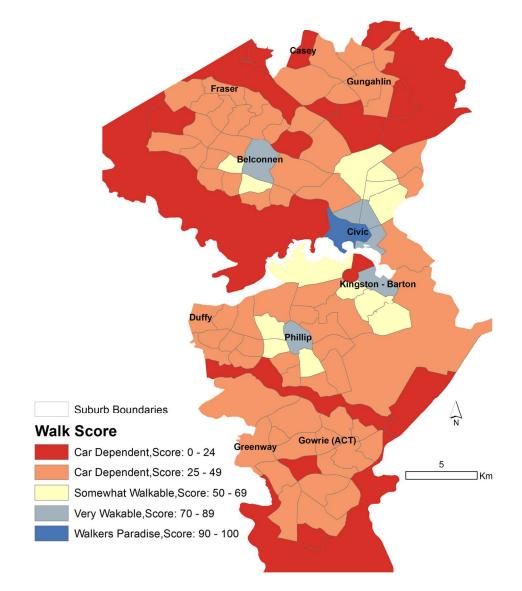


Fig 2: Map of five categories of Walk Score® by ACT suburbs.The five categories are "Walkers Paradise" (Walk Score® 90-100), "Very Walkable" (70-89), "Somewhat walkable" (50 to 69), "Car-dependent" (25 to 49)" and "Car Dependent" (0-24) Link text : "Somewhat walkab

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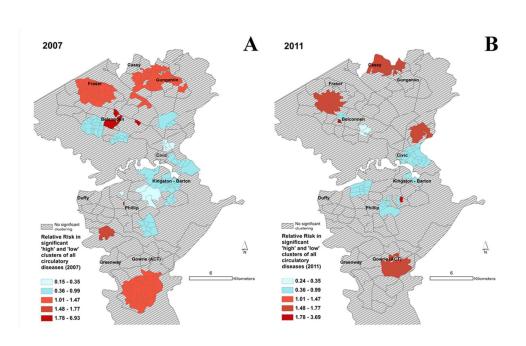
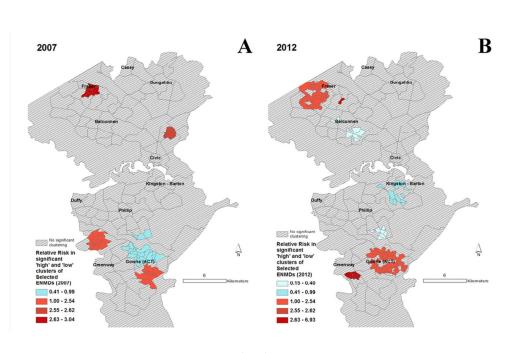


Fig 3: Spatial patterns of CSD risk !! + Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with statistically significantly different risks of hospitalisation for all CSDs. Expected counts for 2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT While maps of all CSDs showed 88x53mm (300 x 300 DPI) BMJ Open: first published as 10.1136/bmjopen-2016-012548 on 8 December 2016. Downloaded from http://bmjopen.bmj.com/ on June 12, 2025 at Agence Bibliographique de I Enseignement Superieur (ABES) . Protected by copyright, including for uses related to text and data mining, Al training, and similar technologies.

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Caption : Fig 4: Spatial patterns of ENMD risk # + # + Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2012* with statistically significantly different risks of hospitalisation for selected ENMDs. Expected counts for 2007 were calculated using 2006 census populations and census 2011 for 2012. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT. * see text for clarification While maps of all CSDs showed

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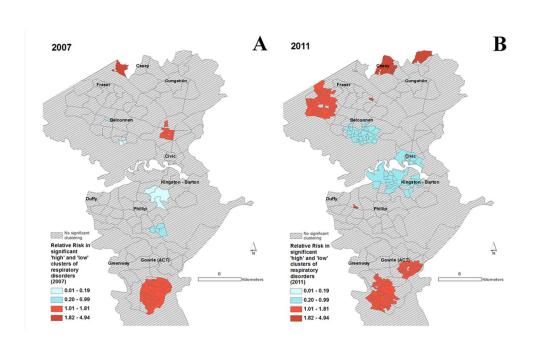


Fig 5: Spatial patterns of respiratory disease risk!! + Maps showing A) clusters of Collection Districts in 2007 and B) Statistical Area 1s in 2011 with statistically significantly different risks of hospitalisation for respiratory diseases. Expected counts for 2007 were calculated using 2006 census populations. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT diseases (Figure 5) or were no 88x53mm (300 x 300 DPI) BMJ Open: first published as 10.1136/bmjopen-2016-012548 on 8 December 2016. Downloaded from http://bmjopen.bmj.com/ on June 12, 2025 at Agence Bibliographique de I Enseignement Superieur (ABES) . Protected by copyright, including for uses related to text and data mining, Al training, and similar technologies.

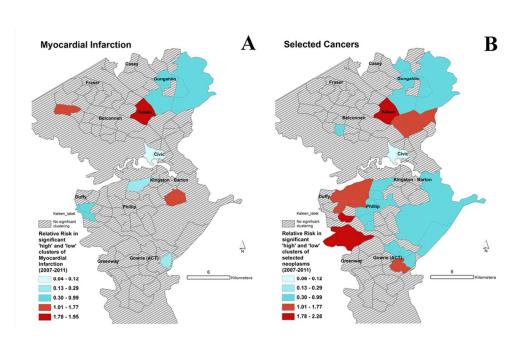


Fig 6: Spatial patterns of MI and cancer risk! + !! + Maps showing Statistical Area 2s (suburbs) with statistically significantly different rates of hospitalisation for A) MI and B) selected cancers. Relative risk for a given contiguous cluster was calculated relative to the risk in the rest of the ACT problems with SaTScan is its p 88x53mm (300 x 300 DPI)

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Table S1.1: Summary of key individual level covariates in hospitalization data

Percent Female	53.55
Percent Married or in De Facto Relationship	48.74
Percent with Private insurance	87.96
Percent with hospital insurance	72.17
Median age	63 years

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		njopen-2016 BMJ Open	Page 3
	ST		
Section/Topic	ltem #	ROBE 2007 (v4) Statement—Checklist of items that should be included in reports of cross-sectional studies Recommendation (a) Indicate the study's design with a commonly used term in the title or the abstract (b) Provide in the abstract an informative and balanced summary of what was done and what value for the scientific background and rationale for the investigation being reported Explain the scientific background and rationale for the investigation being reported State specific objectives, including any prespecified hypotheses	Reported on page #
Title and abstract	1	(a) Indicate the study's design with a commonly used term in the title or the abstract	2 Section 1
		(b) Provide in the abstract an informative and balanced summary of what was done and what vas found	2 Section 1
Introduction		2011 Jner late	
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	3
Objectives	3	State specific objectives, including any prespecified hypotheses	3
Methods		Present key elements of study design early in the paper	
Study design	4	Present key elements of study design early in the paper	4
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, b	4-7
Participants	6	(a) Give the eligibility criteria, and the sources and methods of selection of participants	4-7
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers Give diagnostic criteria, if applicable	4-9
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (meas group and the second secon	4-9
Bias	9	Describe any efforts to address potential sources of bias	10-13
Study size	10	Explain how the study size was arrived at	NA
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which aboutings were chosen and why	4-9
Statistical methods	12	(a) Describe all statistical methods, including those used to control for confounding	10-13
		(b) Describe any methods used to examine subgroups and interactions	NA
		(c) Explain how missing data were addressed	5
		(d) If applicable, describe analytical methods taking account of sampling strategy	NA
		(e) Describe any sensitivity analyses	2 Different models
Results		ap phi que	

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Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, exangined or eligibility,	4-8
		confirmed eligible, included in the study, completing follow-up, and analysed	
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	NA
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information of the social confounders	4-8
		(b) Indicate number of participants with missing data for each variable of interest	4-8
Outcome data	15*	Report numbers of outcome events or summary measures	
Main results	16	(<i>a</i>) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precipion geg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	14-17
		(b) Report category boundaries when continuous variables were categorized	14-17
		(c) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful Here eriod	NA
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyse	NA
Discussion		ning.	
Key results	18	Summarise key results with reference to study objectives	19
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	19-21
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	19-21
Generalisability	21	Discuss the generalisability (external validity) of the study results	19-21
Other information		ar te	
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, original study on	22
		which the present article is based	

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in controls in case-control studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.grg/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

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