Do active modes of transport cause lower body mass index? Findings from the HABITAT longitudinal study

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ABSTRACT

Background: Few studies have examined the causal relationship between transport mode and body mass index (BMI).

Methods: We examined between-person differences and within-person changes in BMI by transport mode over four time-points between 2007 and 2013. Data were from the HABITAT project, a population-representative study of persons aged 40-65 in 2007 (baseline) residing in 200 neighbourhoods in Brisbane, Australia. The analytic sample comprised 9,931 respondents who reported on their main transport for all travel purposes (work- and non-work related). Transport mode was measured as private motor vehicle (PMV), public transport, walking, and cycling. Self-reported height and weight were used to derive BMI. Sex-specific analyses were conducted using multilevel hybrid regression before and after adjustment for time-varying and time-invariant confounders.

Results: Independent of transport mode and after adjustment for confounders, average BMI increased significantly and linearly across the four time-points for both men and women. Men and women who walked or cycled had a significantly lower BMI than their counterparts who used a PMV. BMI was nearly always lower during the time men and women walked or cycled than when they used a PMV; however, few statistically significant differences were observed. For women, BMI was significantly higher during the time they used public transport than when using a PMV.

Conclusion: The findings suggest a causal association between transport mode and BMI and support calls from health authorities to promote walking and cycling for transport as a way of incorporating physical activity into everyday life to reduce the risk of chronic disease.

INTRODUCTION

Active transport – hereby defined as walking, cycling, and public transport - is associated with lower all-cause mortality [1] and a reduced risk of type 2 diabetes [2] and cardiovascular disease.[3] Moreover, the health benefits of active travel accrue independent of leisure-time physical activity.[4] This evidence has prompted calls from the World Health Organisation [5 6] and other international health authorities [7 8] for policy initiatives to promote active transport as a way of incorporating physical activity into everyday life to help address the growing global burden of chronic disease.

One of the pathways linking active transport with reduced rates of chronic disease is likely to be via differences in bodyweight between regular users of active travel and those who rely on private motor vehicles (PMV) as their primary form of transport.[9 10] Cross-sectional research shows that those who use active transport have a significantly lower body mass index (BMI),[11-13] a lower odds of overweight and obesity,[14 15] and a lower percentage body fat [12 13] than PMV users. From a policy perspective, cross-sectional studies are limited because they only *suggest* a causal association between transport mode and bodyweight. In recent years, a small number of longitudinal cohort studies have started to address the causal evidence gap by examining whether change in transport mode is associated with change in bodyweight. Martin et al [16] found that British commuters switching from PMV to active travel significantly reduced BMI, whereas a shift from active travel or public transport to PMV significantly increased BMI. Flint et al [17] reported similar findings. Grøntved et al [18] observed in Sweden that the consistent use of a bicycle to travel to work, or changing from passive travel (car or bus) to cycling, was associated with significantly lower BMI and a low incident risk of obesity at follow-up.

To date, cohort studies of transport mode and BMI have been conducted using only two time-points of data. Moreover, these studies were based on samples of people who commuted to work: this is a somewhat narrow focus as it necessarily excludes large segments of the population such as the unemployed, the retired, and people engaged in full-time home duties. Arguably, studies also need to investigate the relationship between transport mode and bodyweight using representative samples of the general population that include groups inside and outside the paid labour market, and which capture transport use for all purposes (e.g. employment, shopping, socialising, taking children to school). This present study does each of these things using longitudinal data from HABITAT (**H**ow **A**reas in **B**risbane **I**nfluence Heal**T**h and **A**c**T**ivity), a multilevel project investigating the health and well-being of mid-aged men and women living in the Brisbane Local Government Area, Australia.[19] We examine between-person differences and within-person change in BMI by main transport mode over four time-points between 2007 and 2013. Our particular focus is on whether the use of active travel, and change from PMV to active travel, is associated with lower BMI. These issues are investigated using Hybrid Regression, a longitudinal modelling technique that combines the analytic flexibility of random effects analyses (e.g. the specification of multilevel models) with the causal inference strengths of the fixed-effect method (e.g. elimination of omitted variable bias arising from unmeasured time-invariant causes).[20 21] Demonstrating within-person change between transport mode and BMI in the socioeconomically and demographically diverse HABITAT sample will lend further support for a causal interpretation of the relationship, and provide additional evidence to inform policy and planning initiatives directed at shifting transport mode from PMV to active travel.

METHODS

Ethics approval

The HABITAT study received ethical clearance from the Queensland University of Technology Human Research Ethics Committee (Ref. 3967H & 1300000161).

Sample Design

Details about HABITAT's sampling design have been published elsewhere.[19] Briefly, a two-stage probability sampling design was used to select a stratified random sample of 200 neighborhoods (Census Collector's Districts), and from within each neighborhood, a random sample of people aged 40-65 years (on average 85 people per CCD). The baseline HABITAT sample (2007) was broadly representative of the wider Brisbane population.[22]

Data collection and response rates

A structured self-administered questionnaire was sent to 17,000 potentially eligible participants in May 2007 using a mail survey method developed by Dillman.[23] After excluding 873 out-of-scope contacts (i.e. deceased, no longer at the address, unable to participate for health-related reasons) 11,035 usable surveys were returned, yielding a baseline response rate of 68.3%: the corresponding response rates from in-scope and contactable participants in 2009, 2011, and 2013 were 72.6% (n=7,866), 67.3% (n=6,900), and 67.1% (n=6,520) respectively.

Exposure and outcome measurement

Main transport mode. Participants were asked "On most weekdays (Monday to Friday), which type of transport do you mainly use to get to and from places?" Response options included 'Public transport', 'Car or motorcycle', 'Walk', or 'Bicycle'.

Body mass index. This was calculated using self-reported weight in kilograms divided by height in meters squared ($weight_{kg} / height_{m}^2$).

Covariate measurement

Based on previous research [11-17] and our own exploratory analysis, the following factors were treated as potential confounders of the relationship between change in transport mode and BMI change: age, education, employment status, household income, neighbourhood disadvantage; total physical activity; self-rated health, and; private motor vehicle access (details in Online Appendix 1).

Data analysis

Figure 1 in Online Appendix 2 illustrates how the samples for the longitudinal analysis were derived, and identifies the number of cases at each wave after accounting for attrition and excluding those with missing data at all four waves. After exclusions, the baseline analytic sample comprised 4,358 men and 5,573 women: the transport, sociodemographic, physical activity, and health characteristics of the samples and their mean BMIs are presented in Table 1.

Table 1: Transport, sociodemographic, physical activity and health characteristics of the baseline sample (2007) for men and women, by mean (SE) body mass index (BMI)

N=9,931	Men (n=4,358)			Women (n=5,573)		
	%	n	BMI	%	n	BMI
Main transport mode						
Private motor vehicle	80.8	3,521	27.5 (0.08)	82.2	4,578	26.1(0.08)
Public transport	11.8	512	27.4 (0.22)	11.7	650	27.5(0.30)
Walking	2.9	124	26.1 (0.48)	3.5	193	25.1(0.44)
Cycling	2.7	116	25.7 (0.30)	0.4	21	23.5(0.81)
Missing	2.0	85	28.6 (0.69)	2.4	131	27.8(0.72)
Private motor vehicle access						
Always	90.8	3,958	27.4 (0.08)	87.7	4,888	26.1(0.08)
Sometimes	4.8	209	27.6 (0.41)	5.4	302	27.0(0.43)
Never	2.4	103	26.4 (0.51)	2.6	146	28.4(0.71)
Don’t drive	1.6	70	27.8 (0.70)	3.6	202	28.4(0.55)
Missing	0.4	18	28.7 (1.50)	0.6	35	26.5(1.67)
Age						
40 – 44	26.8	1,167	27.3 (0.14)	20.4	1,139	25.6 (0.19)
45 – 49	22.2	967	27.3 (0.15)	21.7	1,209	26.3 (0.18)
50 – 54	20.1	875	27.5 (0.17)	21.2	1,183	26.3 (0.19)
55 – 59	17.6	765	27.5 (0.18)	19.3	1,077	26.6 (0.17)
60 – 65	13.4	584	27.6 (0.22)	17.3	965	26.9 (0.18)

Education (highest level attained)						
Bachelor degree or higher	34.0	1,482	27.0 (0.12)	30.0	1,670	25.5 (0.14)
Diploma/Associate diploma	12.0	524	27.0 (0.19)	11.1	616	25.8 (0.21)
Certificate (trade/business)	21.3	926	27.7 (0.17)	14.5	808	26.4 (0.22)
School	32.7	1,426	27.8 (0.14)	44.5	2,479	27.0 (0.13)
Employment status						
Full-time	73.0	3,180	27.4 (0.08)	37.9	2,111	26.4 (0.14)
Part-time	7.1	308	26.6 (0.28)	23.4	1,303	25.6 (0.15)
Casual	4.0	173	27.0 (0.46)	9.2	510	26.0 (0.27)
Work in a family business without pay	1.2	50	29.2 (0.90)	2.3	129	26.2 (0.51)
Unemployed	1.6	71	27.7 (0.74)	1.4	75	28.9 (0.89)
Permanently unable to work	3.7	159	29.3 (0.54)	2.6	142	30.4 (0.79)
Retired	6.9	301	27.3 (0.30)	10.1	565	26.7 (0.23)
Other: Not in labour force	2.6	112	27.0 (0.55)	13.2	735	26.0 (0.22)
Missing	0.1	4	22.9 (1.17)	0.1	3	21.6 (2.80)
Household income						
$130,000 pa or more	20.2	882	27.5 (0.15)	15.0	833	25.1 (0.17)
$72,800 - $129,999	29.0	1,265	27.4 (0.13)	23.4	1,306	26.2 (0.16)
$52,000 - $72,799	15.2	662	27.3 (0.18)	14.4	801	26.4 (0.20)
$26,000 - $51,999	16.8	731	27.2 (0.20)	19.2	1,071	26.7 (0.20)
$0 - $25,999	7.2	314	28.1 (0.38)	11.0	610	27.8 (0.31)
Don’t know	1.5	67	27.4 (0.87)	3.2	177	27.5 (0.55)
Don’t want to answer this question	8.4	368	27.4 (0.26)	12.2	678	25.6 (0.22)
Missing	1.6	69	27.7 (0.82)	1.7	97	25.4 (0.59)
Neighbourhood disadvantage †						
Q5 (Least disadvantaged)	29.9	1,304	27.2 (0.13)	29.3	1,635	25.5 (0.13)
Q4	19.1	831	27.2 (0.15)	20.1	1,120	25.9 (0.17)
Q3	17.9	779	27.5 (0.18)	16.5	922	26.2 (0.20)
Q2	20.5	892	27.8 (0.20)	20.4	1,135	27.0 (0.19)
Q1 (Most disadvantaged)	12.7	552	27.6 (0.24)	13.7	761	27.8 (0.27)
Total physical activity (MET.minutes/ week) ‡						
<33.3	13.7	596	28.3 (0.23)	14.8	823	27.2 (0.24)
>=33.3 - <250	12.7	552	27.7 (0.23)	12.8	711	27.2 (0.25)
>=250 - < 500	12.1	529	27.6 (0.23)	14.9	829	26.7 (0.22)
>=500 - <1000	16.6	722	27.4 (0.18)	19.1	1,065	26.4 (0.18)
>=1000 - <2000	20.5	893	27.2 (0.16)	19.4	1,079	25.5 (0.15)
>=2000	22.0	957	27.0 (0.14)	16.5	920	25.1 (0.18)
Missing	2.5	109	26.5 (0.36)	2.6	146	26.9 (0.59)
Self-rated health						
Excellent/Very Good/Good	81.9	3,570	27.0 (0.08)	81.7	4,553	25.6 (0.08)
Fair/Poor	17.6	768	29.4 (0.23)	17.5	975	29.5 (0.25)
Missing	0.5	20	26.2 (1.00)	0.8	45	25.2 (0.85)

Prior to analysis, we assessed the likely robustness of the study’s findings to bias resulting from sample attrition (i.e. drop-out) under a Missing at Random (MAR) assumption. Data are considered to be MAR if the probability that the variable is missing does not depend on the value of the variable itself, after controlling for other observed variables.[26] We investigated whether values of transport mode, the covariates, and BMI at one wave predicted dropout at a subsequent wave using multilevel logistic regression with lagged variables. The likelihood of drop out was significantly higher for lower educated groups, members of low income households, those with poorer self-rated health, and persons who reportedly never had access to a PMV; and significantly lower for older people, women, those who mainly walked or cycled for transport, and those whose physical activity levels exceeded 33.3 MET.minutes per week. Importantly, BMI at one wave was not associated with drop-out at a subsequent wave after adjustment for transport mode and the covariates, providing some support for the MAR assumption. When using likelihood-based methods such as random and fixed-effect models (as we do in this study) regression estimates are minimally biased under the MAR pattern.[27]

Analyses proceeds in three stages. First, we use descriptive statistics (means, 95% confidence intervals) to compare the BMI of men and women by main transport mode in 2007 and 2013. Second, we use a transition table to show the amount of stability and change in main transport across adjacent waves between 2007 and 2013. Third, we investigate whether change in transport mode is associated with change in BMI using multilevel hybrid-effect models.[20] Like their fixed-effect counterparts, hybrid models have causal inference strengths by allowing us to estimate within-person change in BMI whilst controlling for changes in measured time-varying observed factors and all-time-invariant observed and unobserved characteristics. The latter feature is especially appealing: by controlling for all person-specific time-invariant factors such as childhood SES, ethnicity, and genetic inheritance, and for factors that are likely to change very slowly over time such as the neighbourhood built environment, we are able to eliminate omitted variable bias that results from possible correlations between these (and other) unobserved factors and the measured variables included in the analyses. The fixed-effect properties of hybrid models are achieved by decomposing each time-varying predictor into two constituent parts: a person-level mean, which captures between-person effects, and a measure of the deviation of each observation from the person-specific mean, which captures the within-person effects (and hence is the causally pertinent aspect of the model).[21] A two-stage modelling strategy was employed. First, we specified a two-level hybrid model (i.e. individuals nested within neighbourhoods) that included a person-level mean and a person-level deviation from the mean for each transport mode; and baseline age (mean centred), and wave measured as 0=2007, 1=2009, 2=2011, and 3=2013. Second, models were adjusted for education and the person-level means and mean-deviations for all time-varying confounders. The between-person transport coefficients for these models are interpreted as the average difference in BMI between a reference group (e.g. PMV user) and the other transport categories over the period 2007-2013. The within-person co-efficient is interpreted as the mean BMI of a person during the time they were using a particular mode of transport (e.g. PMV) differenced from their BMI during the time they were using another mode (e.g. walking). This person-specific difference is then averaged over all persons who (for example) used a PMV at one time-point and who walked at another. We estimated multiple models with different reference categories to compare the BMI of men and women who used transport modes requiring different levels of energy expenditure (e.g. PMV vs walking; public transport vs cycling). All analyses were conducted using Stata/SE 14.1.[28]

RESULTS

Table 2 presents bivariate associations between main transport and BMI for 2007 and 2013. At each time-point, and for both men and women, those who reported walking or cycling had a lower BMI than those who mainly used a PMV. Women who mainly used public transport had a higher average BMI than women who travelled by other means.

Table 2: Main transport mode by mean (95%CI) body mass index for men and women in 2007 (Wave 1) and 2013 (Wave 4)

	Men	Women
2007		
Private motor vehicle	27.5 (27.3 to 27.7)	26.1 (26.0 to 26.3)
Public transport	27.4 (26.9 to 27.8)	27.5 (26.9 to 28.1)
Walking	26.1 (25.2 to 27.0)	25.1 (24.3 to 26.0)
Cycling	25.7 (25.1 to 26.3)	23.5 (21.9 to 25.1)
2013		
Private motor vehicle	27.8 (27.6 to 28.0)	26.7 (26.5 to 26.9)
Public transport	27.8 (27.2 to 28.4)	27.6 (26.9 to 28.3)
Walking	25.6 (24.7 to 26.6)	25.5 (24.3 to 26.7)
Cycling	26.2 (25.2 to 27.2)	24.2 (22.8 to 25.6)

Table 3 presents the extent of stability and change in transport mode for men and women across the four waves. Each row shows the number and percentage of observations using a particular transport mode at one time point (t), and the columns show the number and percentage of observations that changed mode at the next time point (t+1). Among men, there were 5,744 observed occasions of PMV. On 94.8% (n=5,445) of these occasions, the same male was again observed using a PMV at the next wave: and on 3.3% (n=192), 1.2% (n=70), and 0.6% (n=37) of occasions a male was observed changing mode from PMV to public transport, walking, and cycling respectively at the next consecutive wave. Among women, there were 1,141 observed occasions of public transport use. On 69.1% (n=788) of these occasions the same female was again observed using public transport at the next consecutive wave; and on 3.8% (n=43), 0.4% (n=4) and 26.8% (n=306) of occasions a women was observed changing mode from public transport to walking, cycling, and PMV respectively at the next wave.

Table 3: Transport mode stability and change for men and women across any two consecutive data collection waves between 2007 and 2013 †

	Transport mode at *t+1*				
Transport mode at *t*	Private motor vehicle	Public Transport	Walking	Cycling	Total
Men	n (%)	n (%)	n (%)	n (%)	n
Private motor vehicle	5,445 (94.8)	192 (3.3)	70 (1.2)	37 (0.6)	5,744
Public Transport	217 (26.4)	561 (68.3)	29 (3.5)	15 (1.8)	822
Walking	64 (28.2)	26 (11.5)	131 (57.8)	6 (2.6)	227
Cycling	50 (24.3)	19 (9.2)	5 (2.4)	132 (64.1)	206
Total	5,776	798	235	190	6,999
Women					
Private motor vehicle	7,557 (94.8)	304 (3.8)	96 (1.2)	14(0.2)	7,971
Public Transport	306 (26.8)	788 (69.1)	43 (3.8)	4 (0.4)	1,141
Walking	98 (29.9)	49 (14.9)	177 (54.0)	4 (1.2)	328
Cycling	14 (34.2)	3 (7.3)	2 (4.9)	22 (53.7)	41
Total	7,975	1,144	318	44	9,481

† This table shows the total number of wave-to-wave transitions between transport modes for all study participants over 4 waves (irrespective of which waves they transitioned). If a participant experienced multiple transitions, each transition is included in the total.

Table 4 presents the results of the hybrid model analysis for men. Compared with baseline (2007), average BMI was significantly higher in 2011 and 2013 in both the unadjusted and adjusted models. The between-person coefficients showed that men who mainly walked or cycled for transport had a lower average BMI than their counterparts who mainly used a PMV (Model 1) or public transport (Model 2).

The within-person coefficients in Table 4 show that men who used a PMV at one or more waves and public transport, walking or cycling at another wave(s) had lower BMI when using the more active modes (Model 1). These effects were observed prior to and after adjustment for the confounders, however, only the difference between PMV and cycling in the unadjusted analysis reached statistical significance (-0.414kg/m^2, 95%CI -0.72 to -0.10).

Similar findings were observed for men who used public transport at one or more waves and either walked or cycled at another wave(s) (Model 2), and for men who walked at one or more waves and cycled at another (Model 3): for each of these comparisons, BMI was lower when the men used more active modes, although none of the differences were statistically significant.

Table 4: Between-person differences and within-person change in BMI by main transport mode: men, 2007 to 2013

	Unadjusted †		Adjusted ‡	
	β	95% CI	β	95% CI
Model 1§				
Year				
2007	--		--	
2009	0.049	-0.70, 0.16	0.056	-0.06, 0.17
2011	0.145**	0.01, 0.27	0.128**	0.03, 0.25
2013	0.283***	0.15, 0.40	0.252***	0.13, 0.37
Between-person				
Private motor vehicle	--		--	
Public Transport	0.02	-0.41, 0.47	0.01	-0.45, 0.48
Walking	-2.75***	-3.47, -2.03	-2.38***	-3.16, -1.59
Cycling	-1.88***	-2.52, -1.25	-1.44***	-2.20, -0.69
Within-person				
Private motor vehicle	--		--	
Public Transport	-0.057	-0.33, 0.21	-0.223*	-0.48, 0.04
Walking	-0.234	-0.58, 0.12	-0.188	-0.60, 0.23
Cycling	-0.414***	-0.72, -0.10	-0.323	-0.72, 0.08
Model 2				
Between-person				
Public Transport	--			
Walking	-2.78***	-3.63, -1.93	-2.39***	-3.24, -1.55
Cycling	-1.91***	-2.70, -1.12	-1.46***	-2.27, -0.64
Within-person				
Public Transport	--		--	
Walking	-0.177	-0.60, 0.25	0.034	-0.42, 0.49
Cycling	-0.357*	-0.72, 0.01	-0.100	-0.52, 0.32
Model 3				
Between-person				
Walking	--		--	
Cycling	0.865*	-0.09, 1.82	0.936*	-0.05, 1.92
Within-person				
Walking	--		--	
Cycling	-0.179	-0.66, 0.30	-0.134	-0.72, 0.45

† Main transport mode, baseline age (centred) and year (2007=baseline)

‡ Main transport mode, baseline age (centred) and year (2007=baseline), adjusted for education, occupation, household income, neighbourhood disadvantage, total physical activity, self-rated health, and motor vehicle access

§ The BMI differences by year are identical for all models hence the coefficients are presented only once.

*p<0.10, **p<0.05, ***p<0.01

Table 5 presents the results of the hybrid analysis for women. In the unadjusted analyses, BMI increased significantly by an average of 0.274kg/m^2 per women between 2007 and 2009. The corresponding differences in BMI between 2007 and 2011, and 2007 and 2013, were 0.450kg/m^2 and 0.600kg/m^2 respectively. These significant differences remained largely unchanged in magnitude after adjustment. The between-person coefficients show that women who walked or cycled as their main mode of transport had significantly lower BMI than PMV users (Model 1). By contrast, women who mainly used public transport had a significantly higher BMI on average than their counterparts who mainly travelled by PMV (1.25kg/m^2, 95%CI 0.66 to 1.83): this difference was substantially attenuated after adjustment for the confounders however the association remained statistically significant (0.60kg/m^2, 95%CI 0.06 to 1.13). Women who mainly walked or cycled had a significantly lower BMI on average than public transport users (Model 2).

The within-person coefficients in Table 5 show that women who used a PMV at one or more waves and public transport at another wave(s) had higher BMI when using the latter mode (Model 1): this difference reached statistical significance in the adjusted model (0.331kg/m^2, 95%CI 0.04 to 0.65). Women who mainly used a PMV at one or more waves and walked or cycled at another wave(s) had very similar BMI. Model 2 shows that BMI was lower for women during the time when they walked or cycled than when they used public transport: however, the differences did not reach statistical significance in either the unadjusted or adjusted models.

Table 5: Between-person differences and within-person change in BMI by main transport mode: women, 2007 to 2013

	Unadjusted †		Adjusted ‡	
	β	95% CI	β	95% CI
Model 1§				
Year				
2007	--		--	
2009	0.274***	0.15, 0.39	0.265***	0.14, 0.38
2011	0.450***	0.34, 0.55	0.446***	0.33, 0.56
2013	0.600***	0.46, 0.73	0.592***	0.43, 0.74
Between-person				
Private motor vehicle	--		--	
Public Transport	1.25***	0.66, 1.83	0.60**	0.06, 1.13
Walking	-1.91***	-2.77, -1.06	-1.75***	-2.67, -0.83
Cycling	-3.71***	-5.53, -1.89	-1.76*	-3.52, 0.01
Within-person				
Private motor vehicle	--		--	
Public Transport	0.282*	-0.02, 0.59	0.331**	0.04, 0.65
Walking	-0.069	-0.45, 0.32	0.016	-0.41, 0.44
Cycling	-0.028	-0.36, 0.31	0.065	-0.34, 0.47
Model 2				
Between-person				
Public Transport	--		--	
Walking	-3.17***	-4.13, -2.20	-2.35***	-3.34, -1.36
Cycling	-4.96***	-6.89, -3.04	-2.36**	-4.18, -0.54
Within-person				
Public Transport	--		--	
Walking	-0.351	-0.77, 0.07	-0.315	-0.77, 0.14
Cycling	-0.311	-0.71, 0.08	-0.266	-0.74, 0.21
Model 3				
Between-person				
Walking	--			
Cycling	-1.79*	-3.85, 0.25	-0.01	-2.04, 2.03
Within-person				
Walking	--		--	
Cycling	0.040	-0.38, 0.47	0.048	-0.45, 0.55

† Main transport mode, baseline age (centred) and year (2007=baseline)

‡ Main transport mode, baseline age (centred) and year (2007=baseline), adjusted for education, occupation, household income, neighbourhood disadvantage, total physical activity, self-rated health, and motor vehicle access

§ The BMI differences by year are identical for all three models hence the coefficients are presented only once.

*p<0.10, **p<0.05, ***p<0.01

DISCUSSION

Australia, like many other countries, witnessed substantial and rapid rises in overweight and obesity amongst its adult population during the last few decades.[29] Our findings are consistent with this trend: independent of travel mode and after accounting for participants' sociodemographic, health, and physical activity characteristics, BMI increased linearly each wave after baseline (2007). To stem increases in overweight and obesity and address related increases in chronic disease, International and Australian health authorities have called for a shift in transport mode-share from PMV to active travel as a way of routinely incorporating physical activity into everyday life.[5-8] These calls are underpinned and supported by a large body of cross-sectional research showing that those who walk or cycle for transport have lower BMI,[11-13] a lower odds of overweight and obesity,[14 15] and a lower percentage body fat.[12 13] The findings of this present study add to this evidence-base: when averaged over the four waves, BMI was significantly lower for men and women who mainly walked or cycled compared with their counterparts who mainly travelled by PMV.

Prospective research examining the relationship between transport mode and bodyweight has to date been conducted using ecologic designs,[30-32] natural experiments [33 34] and cohort studies.[16-18] These various approaches suggest that population- and individual-level change in the use of active travel or PMV results in a subsequent change in BMI or overweight and obesity. This present longitudinal study builds-on and extends this work. Our use of fixed-effect/hybrid modelling enabled us to estimate within-person change in BMI whilst controlling for concurrent changes in time-varying observed factors (e.g. household income, health) and all time-invariant observed and unobserved characteristics. This approach eliminated omitted variable bias arising from unmeasured time-constant factors, removing a major impediment to valid causal inference from non-experimental data.[21] We found that both men and women who used a PMV at one or more waves, and walked or cycled at another wave(s), had lower BMI when using the active travel modes. The within-person associations often didn't reach statistical significance which may be partly due to limited power to detect effects with low prevalence active transport modes, especially cycling among women. This notwithstanding, all of the differences were in the expected direction in that BMI was lower during the time participants walked or cycled than when they used a PMV.

Two of the known cohort studies of transport mode and BMI [16 17] and most of the cross-sectional research [11-15] find that BMI is lower among adults who commute to work using public transport. In contrast, we found that men who mainly used public transport had a similar BMI to those who travelled by PMV, and men who switched from PMV to public transport (or vice versa) did not experience much change in their BMI. Unexpectedly, among women, users of public transport had higher BMI than their counterparts who mainly travelled by PMV, and those who used a PMV at one or more waves and public transport at another wave(s) had significantly higher BMI during the time they used the latter mode. We speculated that these findings might reflect the socioeconomic characteristics, transport patterns, and BMI profile of women who were not in paid employment. Additional analysis showed that 98.2% of women who mainly used public transport did not have access to a PMV; and women without access to a PMV were less likely to be employed (88.8% vs 95.8%) and more likely to live in a low income household (≤$25,999pa) than those who had access (29.6% vs 9.8%). As a group, women outside the labour market weighed significantly more (1.16kg, 95%CI 0.21 to 2.11) and had higher BMI than employed women (0.75kg/m^2, 95%CI 0.39 to 1.12), particularly those who were unemployed (2.79kg/m^2, 95%CI 1.07 to 4.51) or permanently unable to work (4.17kg/m^2, 95%CI 2.75 to 5.60). We adjusted for these factors: however, both the between- and within-person associations remained statistically significant, suggesting that other processes were at play. This study's findings in relation to public transport use and BMI among women suggest that representative samples of the general population which are used to examine transport use for all daily activities, and commuter samples that are used to examine travel to work, may be capturing different aspects of the relationship between transport mode and BMI hence findings using these two different approaches might not always be directly comparable. This is a question that should be explored in future research, where the focus is on comparing relationships between BMI and transport for different purposes using samples of commuters and the general population.

Study limitations

Main transport mode was self-reported by participants and operationalised relatively crudely using a four- category variable that did not allow for mixed-mode travel (e.g. walking to the bus stop): unmeasured within-mode heterogeneity in transport-related physical activity, leading to an underestimate of the true relationship between transport mode and BMI, was therefore likely.[13] In addition, our measure of transport mode did not allow us to differentiate between different modes of public transport (e.g. bus or train); we were therefore unable to examine the possibility that the use of different modes resulted in concomitant differences in physical activity, and the consequent implications of this for BMI. Height and weight were self-reported and it is well established that the former is often overestimated and the latter underestimated [35] which increases the likelihood that BMI was systematically underestimated. Our finding of an association between transport mode and BMI likely encapsulated residual confounding due to conceptually relevant time-varying factors not being available for analyses. Physical activity was self-reported using questions that asked respondents to estimate the total time they spent walking or doing vigorous or moderate activities in the last 7 days. Retrospective accounts of time-based activities are prone to recall error [36] and the extent and direction of error varies by respondent characteristics such as age and SES.[37] Further, rather than use a covariate that measured LTPA, for data availability reasons, we used a measure of physical activity that captured total activity from four different domains – leisure, occupation, domestic, and transport. This may have resulted in bias due to differential misclassification leading to an underestimation of the association between transport mode and BMI.

CONCLUSION

The vast majority (>80%) of mid-aged residents of Brisbane used a private motor vehicle as their main mode of transport, and approximately one-in-ten mainly travelled by public transport: only a small minority (<5%) of residents walked or cycled. Men and women who mainly walked or cycled had a lower BMI than their counterparts who used more passive forms of transport; and people who changed from a passive mode to walking or cycling had a lower BMI when using these more active modes (after adjustment for relevant time-invariant and time-varying confounders). Taken together, these results suggest a causal relationship between transport-related physical activity and bodyweight. This, in conjunction with the low prevalence of walking and cycling for transport, highlights an urgent need for governments to plan, invest in, and design urban environments that facilitate walking and cycling to promote health and prevent chronic disease;[38] doing so will also help address other serious societal challenges such as fossil fuel dependency, rising greenhouse gas emissions, traffic congestion, and air and noise pollution.[39]

What is already known on this subject?

The few cohort studies find that changing from private motor vehicle to active travel (walking and cycling) is associated with reductions in body mass index. To date, this work has been conducted in the UK and Sweden using a small number of time-points (t=2), it has focused exclusively on commuting (i.e. travel to work), and is based on analyses that weren't stratified by sex.

What this study adds

This Australian cohort study finds that body mass index increased for men and women over four time-points between 2007 and 2013. Men and women who walked or cycled had a lower body mass index than their counterparts who used a private motor vehicle. Body mass index was lower for men and women during the time they walked or cycled than when they used a private motor vehicle or public transport. The analyses were based on a population-representative sample of employed and non-employed persons who reported on their transport use for all activities of daily life (work and non-work related). The findings support the promotion of active travel as a way of incorporating physical activity into everyday life to address rising rates of overweight and obesity and related chronic disease.

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