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The Influence of working from home on the number of commuting and non-commuting trips by workers during 2020 and 2021 pre- and post-lockdown in Australia

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TITLE:	The Influence of working from home on the number of commuting and non-commuting trips by workers during 2020 and 2021 pre- and post-lockdown in Australia

ABSTRACT:

Since the start of 2020, we have seen major changes in the way communities operate. Mobility behaviour has been drastically impacted by work from home (WFH) and by lockdowns and restrictions in different jurisdictions. This study investigates the influence of WFH and different lockdown patterns on commuting and non-commuting trips in Australia by workers between early 2020 and late 2021. The data includes three waves of data collection to represent different lockdown periods. A multiple discrete-continuous extreme value (MDCEV) model is estimated to represent the number of one-way trips undertaken weekly with different purposes (commuting, work-related, education, shopping, personal business/social recreation), and by different modes (car, public transport, active modes). Explanatory variables include socioeconomic characteristics, location, the time period during the pandemic (i.e., waves), and latent variables. The results suggest that across all waves and jurisdictions, respondents that WFH more often are more likely to undertake relatively more shopping trips and personal business/social recreation trips, perhaps substituting these trips in replacement of their lesser commuting trips. Interestingly, all other influence held constant, individuals who are more concerned about the use of public transport are more likely to undertake commuting trips by all modes, more likely to do shopping trips, and less likely to undertake personal business/social recreation trips – suggesting they are prioritising essential trips rather than social/personal trips.

KEY WORDS: ***COVID-19; working form home; Australian experience; commuting trips; non-commuting trips; productivity; public transport implications***

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1. Introduction

The COVID-19 pandemic has reshaped the way we live and travel, possibly for many years to come. The 'New Normal' seems to be one that is best associated with living with COVID-19 rather that 'after COVID-19'. After more than two years since the pandemic spread throughout the world, we have amassed a significant amount of evidence on what this is likely to mean for patterns of commuting activity in a setting where working for home (WFH) is becoming a more popular and legitimate alternative to choosing to commute. With WFH continuing to some extent as a non-stigmatised alternative to going to the regular office, non-commuting travel is also likely to change as workers and their families have greater flexibility in how they schedule that other travel activity. Moreover, in Australia the pandemic has also seen a significant model shift from public transport to the car, followed by active modes to a lesser extent.

In this paper we develop a series of trip making models for workers in New South Wales and Queensland in a metropolitan setting, using three waves of data: the first one was collected between September-October 2020 when there were relatively minor restrictions in Australia; between March-May 2021, a period at the start of what would be the longest sustained period of lockdown in New South Wales (with relative freedoms still existing in Queensland throughout the same time period); and November-December 2021, the period at the end of this prolonged lockdown in New South Wales. Given the mix of lockdown conditions and COVID case numbers in the two jurisdictions of these time periods, multiple comparisons can be made under different government enforced restrictions.

A multiple discrete-continuous extreme value (MDCEV) model is estimated to represent how respondents assign their mobility patterns in fifteen different alternatives representing five purpose types and three modes of transport. The trip purposes are commuting, work-related, education, shopping and personal business/social recreation trips; while the modes are car, public transport and active modes. This model allows us to understand both the discrete choice of making certain type of one-way trips by different modes, and the continuous choice of how much of those trips to do weekly. The differing patterns of travel activity are explained by different socioeconomic, geographic, and attitudinal variables to gain a better understanding on what is driving the levels of trip-purpose-mode-specific travel during the pandemic, before and after lockdown periods. The attitudinal variables include concern towards the use of public transport due to hygiene and the number of people using it, life satisfaction, attitudes towards authorities/government and community response to the pandemic, and attitudes towards social or massive meetings. Different scenarios are simulated to analyse the influence of the different explanatory variables on the average number of one-way trips for each purpose and mode.

The paper is organised as follows. The next section presents a brief literature review of the number of trips models using MDCEV models and the influence of COVID-19 and working from home. Section 3 describes the data used in this study. The fourth section presents the methodology to estimate the MDCEV models and to obtain the latent variables using factor analysis. Section 5 presents the model results, while section 6 presents the simulated scenarios. The final section discusses the main findings of this research.

2. Literature review

Since the start of COVID-19, a significant amount of literature has focused on understanding the influence that it has had on mobility patterns in different context around the world (Beck et al., 2020; Beck & Hensher, 2020; Hensher et al., 2021a; Balbontin et al., 2021; Barbieri et al., 2021; Zhang et al., 2021; Vallejo-Borda et al., 2022). This section will briefly review studies that have specifically focused on the link between commuting and non-commuting trips.

Astroza et al. (2020) compare the number of trips by purpose and mode between a normal week and during the first week of COVID-19 restrictions in Santiago, Chile during March 2020. They used jointly estimated binary probit (BP) and linear regression models. The dependent variable of the BP model is to WFH or not, and the dependent variable for the regression model is the number of trips other than work or study (i.e., shopping, errands, medical, leisure). Their results suggest that individuals with higher incomes and a higher education level are more likely to WFH, and people that WFH more are less likely to do non-commuting trips. Fatmi (2020) studies the daily travel activities during COVID-19 travel restrictions in the Kelowna region of British Columbia, Canada during March to May 2020. Their results show that participation in activities outside of home was reduced by more than 50%, and the most frequent trips were due to routine shopping, followed by work-related trips. In terms of recreational and social activities, the number of trips seemed to increase for a higher share of older adults, while it decreased for a higher share of younger adults. Jiao & Azimian (2021) study the changes in travel behaviour in the second phase of the COVID-19 pandemic in the United States. They estimate two binary logit models using as dependent variables dummy variables equal to 1 if they travelled less to stores and by public transport during the second phase of the pandemic than pre-pandemic. Their results show that older respondents less likely to travel to stores during the second phase of the pandemic, and less likely to use public transport for these trips. Individuals without a graduate degree were less likely to reduce their trips to a store and by public transport. Individuals in larger households were more likely to travel to stores and by public transport. Politis et al. (2021) use data collected in two waves in Thessaloniki, Greece: one year before and during the COVID-19 lockdown of April 2020. They used regression models and cox proportional hazards duration models to analyse travel behaviour. Results showed that the average daily trips per person decreased by 50% during lockdown, which was much higher for non-commuting trips. In terms of modes of transport used, the share of walking trips increased, private car was also increased mostly for commuting trips, and the use of public transport decreased significantly.

Bhat et al. (2016) propose a method for a finite discrete mixture of normal version of the multiple discrete-continuous probit model using travel survey data in New Zealand. Their framework and results allow for a better understanding on the influences of individual preferences for tourism destinations. These types of models have been used widely in time allocation by activity type studies (Pinjari et al., 2009; Pinjari & Bhat, 2010a; Calastri et al., 2017; Jokubauskaitė et al., 2019; Palma et al., 2021). Bhaduri et al. (2020) use an MDCEV model to explain the mode choice and frequency of use for weekly trips including work from home across various cities in India during March-April 2020. The trips included commuting trips by mode and other discretionary activities, where each alternative represented work from home or a mode of transport. Their results show that inertia has a higher influence on commuting trip rather than on discretionary trips; and inertia is higher for car and motorbike of longer trips. Results show that modes with lower levels of social distancing, such as public transport, have a lower inertia; and those middle-aged adults are more likely to use car than other respondents.

This section briefly described studies that have focused on the number of trips or used MDCEV models. The contribution of our article is to use an MDCEV model to understand the effect of COVID-19 in commuting and non-commuting travel behaviour by mode using mode-purpose-specific alternatives and using data from different periods during the pandemic.

3. Data description

The data used in this study was collected as part of a larger study in Australia to understand the influence of work from home in the transport network (Beck et al., 2020; Beck & Hensher, 2020; Hensher et al., 2021; Balbontin et al., 2022). In this paper we develop a series of trip making models for workers in The Greater Sydney Metropolitan area (GSMA) in New South Wales (henceforth referred to as GSMA) and South East Queensland (henceforth referred to as SEQ), using three waves of data: Wave A, B and C. Wave A was collected during August-September 2020, when there were relatively minor restrictions in Australia; Wave B was collected on April-May 2021, a period at the start of what would be the longest sustained period of lockdown in NSW (with relative freedoms still existing in QLD throughout the same time period); and Wave C was collected during December 2021, the period at the end of this prolonged lockdown in NSW. Given the mix of lockdown conditions and COVID case numbers in the two jurisdictions of these time periods, multiple comparisons can be made under different government enforced restrictions. The three waves of data were collected using an online survey that contained different questions regarding respondents' work, travel behaviour, attitudes towards the pandemic and socioeconomics. Wave A data contains 661 workers, Wave B and Wave C each contain 645 workers.

Figure 1 represents the number of one-way weekly trips by mode and purpose for each wave and jurisdiction. Wave A is relatively similar between GSMA and SEQ, although respondents in GSMA usually make slightly more work-related one-way trips and in SEQ do more education trips. In Wave B, where GSMA was starting its longest lockdown period and SEQ had more freedoms, respondents in SEQ make significantly more commuting trips, particularly by car, while respondents in GSMA seem to undertake more shopping trips. In Wave C, at the end of this lockdown, respondents in GSMA and SEQ both did fewer commuting trips by car than in Wave B, but more trips in public transport; and shopping trips by car increased in SEQ while they decreased in GSMA.

The survey included attitudinal questions to understand respondents' attitudes towards the government and authorities' response to the pandemic, their level of comfort associated with undertaking different types of activities, their level of satisfaction with life in general, and their concern towards the use of public transport due to the pandemic. These questions were used to construct the latent variables, which will be detailed in section 1.2, but the average score (between 1 and 5) for these questions is presented in Figure 2. Results show that during the first year of the pandemic, in Wave A, respondents in GSMA and SEQ were significantly more concerned about using public transport, which decreased and remained around three points in Waves B and C – although respondents in SEQ seem a bit less concerned than in GSMA.

In terms of satisfaction with life and support towards authorities/government and community response, the level has remained relatively the same across all Waves, although satisfaction with life in general has increased slightly in Wave C while support for the government and community response has decreased. In terms of level of comfort associated with undertaking different activities, in both states, respondents seem much more comfortable in participating in small social group-based meetings (friends and family) as compared to large gatherings of people (e.g., concerts, watching professional sports live, live entertainment), and respondents feel more comfortable in the last two Waves relative to the Wave A.

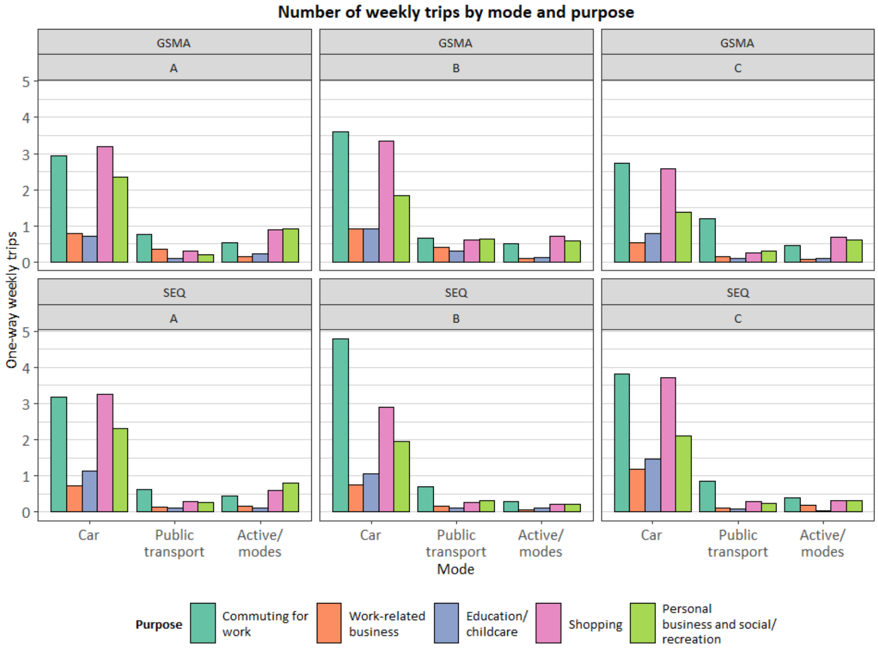

Figure 1. Number of weekly one-way trips by mode and purpose

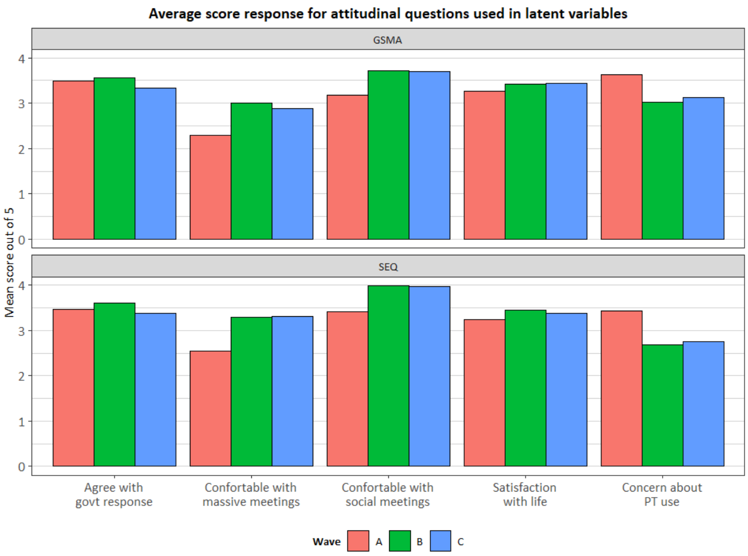

Figure 2. Average score response for attitudinal questions used in defining the latent variables

General descriptives of respondents are presented in Table 1. The average levels are relatively stable across waves and states, although average personal income is slightly lower in SEQ than in GSMA (a disparity that is also reflected in Census data). In terms of days working from home (WFH), during the first year of the pandemic, the average days WFH are close to two days a week, while in Wave B it decreased significantly to 1.33 for GSMA and 0.85 for SEQ. This is expected as GSMA was at the beginning of a lockdown phase. In Wave C, the averages increased again reaching 1.66 in GSMA and 1.28 in SEQ.

Table 1. General descriptives - mean (standard deviation)

	Wave A		Wave B		Wave C	
	GSMA	**SEQ**	**GSMA**	**SEQ**	**GSMA**	**SEQ**
Age (years old)	40.48 (13.48)	40.45 (13.74)	41.23 (14.59)	41.88 (13.33)	44.87 (14.77)	40.97 (13.83)
Gender: male (1,0)	41%	31%	48%	41%	46%	35%
Income ('00AUD$) personal	81.65 (55.83)	73.40 (45.68)	83.87 (52.32)	77.97 (54.33)	84.67 (61.66)	83.86 (59.90)
Occupation manager (1,0)	16%	13%	18%	11%	20%	18%
Occupation professional (1,0)	31%	32%	30%	28%	29%	29%
Occupation blue collar (1,0)	13%	15%	14%	18%	17%	13%
Distance from home to work (kms)	19.11 (25.70)	21.39 (65.92)	17.50 (20.83)	18.25 (18.15)	17.36 (17.10)	14.75 (14.31)
Number of days WFH last week	2.09 (2.28)	2.00 (2.33)	1.33 (1.90)	0.85 (1.57)	1.66 (2.07)	1.28 (1.90)
Number of days worked last week	4.61 (1.36)	4.67 (1.29)	4.25 (1.48)	4.29 (1.40)	4.10 (1.54)	4.42 (1.51)
Number of respondents	373	288	351	294	297	348

Table 2 presents the percentage of respondents that do at least one trip for each purpose-mode, and the average number of trips that these respondents undertake. The average number of commuting trips has not changed significantly across waves – with the exception of Wave B public transport trips – but the percentage of respondents that commute reached a maximum in Wave B where 90% of respondents commuted at least once. In Wave B, the percentage of respondents using car to commute was the highest at 71%, while in Waves A and B it is around 68%.

Table 2: Percentage of respondents that do at least one trip for each purpose-mode and the number of one-way trips

	Wave A		Wave B		Wave C	
	%	**N Trips**	**%**	**N Trips**	**%**	**N Trips**
Commute by car	50%	6.08 (3.88)	64%	6.44 (4.13)	53%	6.28 (3.80)
Commute by public transport	13%	5.53 (4.06)	16%	4.33 (2.92)	17%	5.86 (3.54)
Commute by active modes	11%	4.57 (3.89)	10%	3.91 (3.16)	8%	5.09 (3.34)
Work-related trips by car	20%	3.74 (5.16)	20%	4.09 (5.79)	20%	4.44 (5.88)
Work-related trips by public transport	5%	4.89 (9.56)	8%	3.67 (2.61)	4%	3.04 (2.28)
Work-related trips by active modes	5%	3.39 (3.55)	6%	1.51 (1.02)	3%	4.70 (5.82)
Education trips by car	18%	5.02 (3.45)	21%	4.59 (3.74)	21%	5.46 (3.89)
Education trips by public transport	3%	2.87 (1.94)	6%	3.26 (2.23)	4%	2.50 (1.64)
Education trips by active modes	4%	4.00 (3.64)	6%	1.90 (2.00)	2%	3.23 (2.35)
Shopping trips by car	74%	4.37 (4.41)	77%	4.10 (3.50)	71%	4.50 (3.24)
Shopping trips by public transport	8%	3.93 (2.89)	9%	4.85 (2.69)	7%	3.67 (2.94)
Shopping trips by active modes	20%	3.88 (3.24)	14%	3.50 (3.59)	12%	3.93 (2.87)
Social recreation/personal business trips by car	58%	4.01 (3.90)	55%	3.39 (2.78)	48%	3.70 (2.88)
Social recreation/personal business trips by public transport	9%	2.73 (2.03)	10%	4.82 (3.20)	9%	3.14 (2.47)
Social recreation/personal business trips by active modes	17%	4.98 (4.72)	13%	3.33 (2.39)	10%	4.37 (3.53)

The second most frequent trip refers to shopping trips, which are in their majority made by car. The data shows significant differences across waves and jurisdictions in terms of commuting and non-commuting travel behaviour, which will be analysed with more detail in the next sections. A similar table but separated by region is presented in Table 10 in the Appendix. The main difference across jurisdictions can be found in commuting trips by car, which is significantly higher in SEQ than in GSMA in Wave B (70% versus 60%) and in Wave C (59% versus 45%). The use of car for shopping trips is significantly higher in SEQ than in the GSMA for Wave C (79% versus 61%), and significantly lower for shopping trips in active modes (8% versus 17%).

4. Methodology

1.1 Modelling framework

The overall modelling framework is presented in Figure 3. The proposed framework focuses on the decision to choose to undertake a one-way trip by purpose and mode. The respondent characteristics z_q, such as their age, gender, occupation, location (state), as well as their latent attitudes LV_q (e.g., level of comfort going out to social meetings, level of concern towards the use of public transport, level of life satisfaction, among others), and the lockdown conditions defined by the waves of data D_W, determine the propensity to undertake on-way trips for each purpose by each mode. Error terms are associated with trip purpose type η_p, mode η_m, and the relative utility of each alternative, U_{pm}. The combination of the purposes and modes generates a total of fifteen alternatives, which are presented in Figure 4.

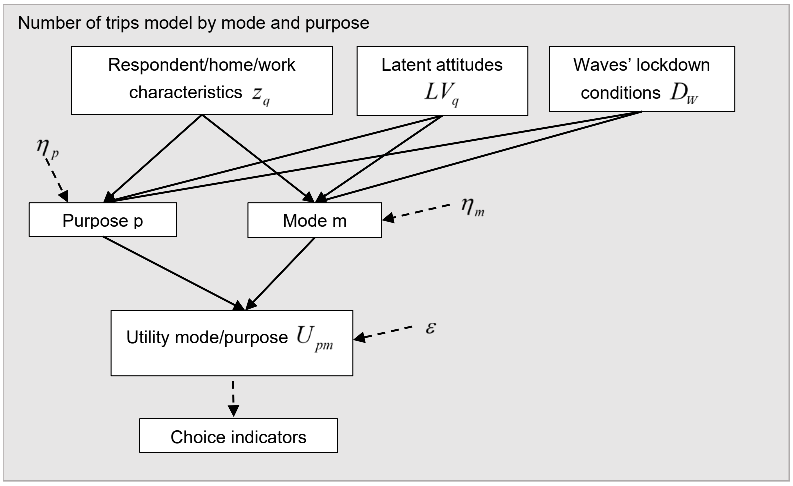

Figure 3. Mode and purpose number of one-way trips model structure

Each alternative is represented by two subindexes: one associated with the mode of transport used *m* ($m = 1,...,M$); and the other with the travel purpose *p* ($p = 1,...,P$). The multiple discrete-continuous extreme value (MDCEV) model used in this study was originally proposed by Bhat (2005) and later extended in Bhat (2008) where the utility function is defined as the sum over all purposes and modes, as follows:

$$U(x) = \sum_{p=1}^{P}\sum_{m=1}^{M}\frac{\gamma_{pm}}{\alpha_{pm}}\psi_{pm}\left\{\left(\frac{x_{pm}}{\gamma_{pm}}+1\right)^{\alpha_{pm}}-1\right\} \quad (1)$$

subject to the budget constraint:

$$\sum_{p=1}^{P}\sum_{m=1}^{M} x_{pm} p_{pm} = B \tag{2}$$

where $\psi_{pm} = \exp(V_{pm} + \varepsilon_{pm})$ (3)

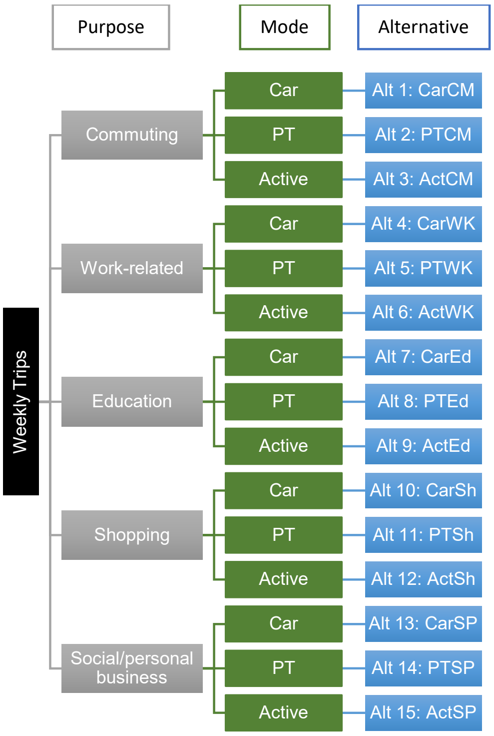

Figure 4. Alternatives definition

The budget B is represented by the total number of one-way trips made by an individual last week. That is, it is assumed that individuals have a mobility pattern that is relatively stable, and they can choose how to distribute the total budget (i.e., how many trips by each purpose and mode to do weekly). P represents the number of purposes and M the number of modes, so the combined *pm* represents the different alternatives; x_{pm} is the number of weekly one-way trips by purpose *p* and mode *m*; p_{pm} is the unit cost of alternative *pm,* which is assumed equal to 1 since all alternatives have the same influence on the mobility budget; ψ_{pm} refers to the baseline utility parameters which represent the marginal utility of one unit of consumption of alternative *pm* at the point of zero consumption for that alternative; V_{pm} determines the alternatives' deterministic base utility and ε_{pm} is an independent and identically distributed random term with a Gumbel distribution with mean zero and a unit variance. α_{pm} and γ_{pm} are parameters that determine control satiation of each alternative, which shows the added benefit to the baseline utility of one additional trip, and γ_{pm} enables corner solutions. These satiation parameters operate differently theoretically, but empirically it is difficult to disentangle the two effects, as discussed in Bhat (2008), and with this in mind we estimate a generic $\alpha_{pm} = \alpha, \forall p, m$ and alternative-specific γ_{pm}. Equations (1) and (2) are revised as follows:

$$U(x) = \sum_{p=1}^{P}\sum_{m=1}^{M} \frac{\gamma_{pm}}{\alpha} \psi_{pm} \left\{ \left(\frac{x_{pm}}{\gamma_{pm}} + 1 \right)^{\alpha} - 1 \right\} \tag{4}$$

subject to the budget constraint:

$$\sum_{p=1}^{P}\sum_{m=1}^{M} x_{pm} = B \tag{5}$$

As $\alpha \to 0$ equation (4) collapses to a linear expenditure system as follows (Bhat, 2008):

$$U(x) = \sum_{p=1}^{P}\sum_{m=1}^{M} \gamma_{pm}\psi_{pm} \ln\left(\frac{x_{pm}}{\gamma_{pm}} + 1\right) \tag{6}$$

The deterministic baseline utility function V_{pm} for each alternative *pm* (purpose and mode) and individual *q* is defined as:

$$V_{pm} = ASC_{pm} + \sum_{j}\left(\beta_{mj} z_{qj} + \beta_{pj} z_{qj}\right) + \sum_{i}\left(\beta_{mi} LV_{qi} + \beta_{pi} LV_{qi}\right) + \beta_{WB} \cdot D_{WB} + \beta_{WA} \cdot D_{WA} + \eta_p + \eta_m \tag{7}$$

ASC is the alternative specific constant; z_{qj} represent different variables related to the individual characteristics, such as income, age, gender, occupation, proportion of days that they work from home (WFH), among others; LV_{qi} represent latent variables included in the model, as will be explained in the following subsection; β_{mj} and β_{pj} represent the parameter estimates associated with the individual characteristics z_{qj} or latent factors LV_{qi} which are common for mode *m*, and purpose *p*, respectively; D_{WB} and D_{WA} represent dummy variables equal to 1 if the respondent belongs to data wave A or B, respectively, and β are its associated parameter estimates; η_p and η_m represent the error components associated to mode *m* and purpose *p*, respectively.

1.2 Latent variables estimated using factor analysis

Respondents were asked to answer several attitudinal questions that referred to their concern about using public transport (PT), their attitude towards social or massive meetings (WFH), concern about health due to COVID-19, among others. We used the Kaiser-Meyer-Olkim (KMO) test to measure sampling adequacy (Kaiser & Rice, 1974) and Bartlett's Test of Sphericity (Bartlett, 1951) – which showed that factor analysis might be useful with our data. All the attitudinal questions were analysed using parallel analysis to identify the number of latent variables (Horn, 1965). This analysis suggested five latent variables should be used to represent respondents' attitudes. The method of extraction is maximum log-likelihood with oblique rotation given that there might be some correlation between these attitudes. The five latent variables extracted are represented as follows[1]:

1. Authorities and community's response supporters: respondents that believe the authorities and community response towards the pandemic has been appropriate.
2. Massive meeting lovers: respondents that feel comfortable having any type of meeting, including music events, watching live entertainment, among others.
3. Social meeting lovers: respondents that feel comfortable having social meetings with friends, visiting restaurants and pubs, gyms and exercise groups, among others.
4. High level of life satisfactions: respondents that said to be satisfied and happy with their life.

[1] These factors were extracted using all the Waves together. However, the same latent factors emerge within each Wave of data, which shows their robustness.

5. Concerned about public transport: people that are concerned about hygiene and the number of people in public transport due to COVID-19.

The attitudinal questions defining each latent variable and their weights are shown in Table 3 to Table 7. The higher weights in the second latent variable, related to support towards the authorities and community's response to the crisis, refer to the response of other people to COVID-19 (if they have been appropriately self-distancing, self-isolating, etc.), and if the response of the wider community and government has been appropriate.

Table 3. Survey questions associated latent variable authorities and community's response supporters

Survey question	Weight
The Federal government response to Covid-19 has been appropriate	0.72
The State government response to Covid-19 has been appropriate	0.70
The response of business to Covid-19 has been appropriate	0.74
The response of the wider community to Covid-19 has been appropriate	0.73
People have been appropriately social distancing as a measure to combat Covid-19	0.66
People have been appropriately self-isolating as a measure to combat Covid-19	0.67
I trust governments to respond to Covid-19 in the future	0.80
I trust business to respond to Covid-19 in the future	0.79
I trust other people to respond to Covid-19 in the future	0.72

Scale: Strongly disagree (1), Disagree (2), Somewhat disagree (3), Neither agree nor disagree (4), Somewhat agree (5), Agree (6), Strongly agree (7)

The second and third latent variables refer to how comfortable respondents feel with different types of meetings. These latent variables might seem similar, but the parallel analysis suggested that they should be considered separately: i.e., respondents that feel comfortable in smaller social meetings do not necessarily feel comfortable in massive events, and vice versa.

Table 4. Survey questions associated with the latent variable massive meeting lovers

Survey question	Weight
If someone asked you to each of the following, how comfortable would you feel about undertaking these day-to-day activities at the moment?	
Watching professional sport	0.78
Music events	0.93
Watching live entertainment	0.92
Playing organised sport	0.61

Scale: Very uncomfortable (1), Uncomfortable (2), Somewhat uncomfortable (3), Neither (4), Somewhat comfortable (5), Comfortable (6), Very comfortable (7)

Table 5. Survey questions associated with latent variable social meeting lovers

Survey question	Weight
If someone asked you to each of the following, how comfortable would you feel about undertaking these day-to-day activities at the moment?	
Meeting with friends	0.82
Visiting restaurants	0.77
Going to the shops	0.75

Scale: Very uncomfortable (1), Uncomfortable (2), Somewhat uncomfortable (3), Neither (4), Somewhat comfortable (5), Comfortable (6), Very comfortable (7)

The fourth latent variable represents respondents that seem to be satisfied and happy with their life nowadays. The fifth latent variable refers to health concern and is defined by how a person thinks about COVID-19 as a serious public health concern which requires drastic measures to be taken. The last factor relates to a concern about the use of public transport (PT), defined by the concern about hygiene and the number of people using PT.

Table 6. Survey questions associated with latent variable high level of life satisfaction

Survey question	Weight
How satisfied are you with your life nowadays?	0.88
How worthwhile do you think the things that you do in life are?	0.84
How happy did you feel yesterday?	0.86

**Scale from 0 (not at all satisfied) to 10 (completely satisfied)

Table 7: Survey questions associated with latent variable concerned about PT

Survey question	Weight
Imagine you had to catch public transport tomorrow, what would be your level of concern about hygiene be?	0.94
Imagine you had to catch public transport tomorrow, what would be your level of concern about the number of people using public transport?	0.96

Scale: Not at all concerned (1), Slightly concerned (2), Somewhat concerned (3), Moderately concerned (4), Extremely concerned (5)

5. Model results

The model results for the deterministic part of the utility function V_{pm} are presented in Table 8. Candidate sociodemographic characteristics (presented in Table 1), wave dummy variables, and latent variables were included in each alternative. Other potential influences that are not presented were not statistically different from zero (e.g., income, location dummy variables), and are excluded from the final model. Similarly, four error components were identified as statistically significant, associated with the car for all trip purposes, and specific trip purposes for all modes, namely commuting work-related or education trip purposes. This suggests that there is a correlation between the car trips, regardless of the trip purpose; between the commuting, work-related and education trips, regardless of the mode used to make them. The results show that male respondents are more likely to undertake work-related trips, and individuals that work as managers or in blue collar occupations (i.e., technicians and trades workers, machinery operators and drivers, and labourers) are also more likely to undertake work-related trips. Age is negatively correlated with the number of education trips made weekly. The distance from home to work has a positive influence on all trips made by car, which suggests that individuals that live further away from home are more likely to use their car for all trips than other modes. The proportion of days working from home (WFH) has a negative influence on all trips made by car and as expected, a negative influence on the number of commuting trips by all modes.

The latent variable results suggest that:

- Individuals who support the authorities/government and community response to the pandemic are less likely to undertake commuting and shopping trips (government health messaging asked people to reduce travel activity wherever possible; for a long period of time only shopping for necessities and essential commuting was permitted, so it is logical that those who expressed positive support for the government action would also similarity attempt to reduce activity in line with what was recommended by authorities).

- Respondents that feel comfortable attending massive meetings are more likely to use public transport for all their trips (not surprising as if they are comfortable in large crowds, they would have less qualms about using public transport) and are less likely to undertake commuting and shopping trips.
- Those that feel comfortable going to social meetings are more likely to use the car on all such trips (likely as these small group social meetings are in local areas and not readily served by public transport, additionally these smaller meetings are typically with family and friends and not strangers that one may encounter on public transport) and are less likely to do all but social recreation/personal business trips.
- Respondents that said they are satisfied with their life nowadays are less likely to undertake commuting, work-related and shopping trips (likely a function of still being able to complete meaningful work from home and are more able to accommodate the reduced amount of travel activity and social contact – perhaps finding the latter to be less important to their overall mental wellbeing than others).
- Finally, respondents that said they are concerned about using public transport are more likely to undertake trips for all purposes except social recreation/personal business (likely respondents concerned about the use of public transport will avoid leaving their houses if they do not believe it is necessary, which is usually associated to social or personal trips).

The wave dummy variables suggest that participants in Wave A were less likely to undertake all but social recreation/personal business trips relative to Wave C – which suggests that, even when restrictions were not as strict during the first wave, people were working from home more frequently and avoiding work-related or shopping trips, prioritising their social and personal business trips. Results show that in Wave B respondents were less likely to undertake commuting or shopping trips and more likely to use public transport relative to Wave C, likely related to the fact that Wave B was collected at the start of the longest lockdown in NSW and QLD had relative freedoms, where WFH had increased given authorities' indications, and people were probably avoiding shopping and public transport where they had contact with strangers. In separate work focusing on public transport usage through the pandemic, we have shown that those who need to use public transport for trip making (essential workers, those on lower incomes) are among those who are most concerned about the biosecurity of public transport (Beck at al. 2022).

Table 8. Model results MCDEV deterministic utility function – mean (t-value)

Description	Mode	Purpose	Mean	T-value
ASC	Car	Commuting	1.08	13.73
ASC	PT	Commuting	0.77	6.00
ASC	Active modes	Commuting	-0.20	-1.63
ASC	Car	Work-related	-2.14	-17.22
ASC	PT	Work-related	-2.60	-13.96
ASC	Active modes	Work-related	-2.93	-15.68
ASC	Car	Education	-0.95	-5.29
ASC	PT	Education	-1.60	-7.31
ASC	Active modes	Education	-1.75	-7.93
ASC	Car	Shopping	1.34	16.37
ASC	PT	Shopping	-1.15	-8.95

Description	**Mode**	**Purpose**	**Mean**	**T-value**
ASC	Active modes	Shopping	-0.40	-3.44
ASC	PT	Social/personal business	-1.23	-10.45
ASC	Active modes	Social/personal business	-0.82	-7.62
Male (1,0)	All	Work-related	0.54	4.87
Profession manager (1,0)	All	Work-related	0.55	4.10
Profession blue collar (1,0)	All	Work-related	0.49	3.38
Age (years)	All	Education	-0.02	-4.32
Distance from home to work (kms)	Car	All	0.002	2.03
Proportion of WFH	Car	All	-0.43	-3.79
Proportion of WFH	All	Commuting	-2.97	-26.11
Latent variable support government/authorities' response	All	Commuting	-0.09	-2.46
Latent variable support government/authorities' response	All	Shopping	-0.07	-2.03
Latent variable massive meetings lover	PT	All	0.12	3.14
Latent variable massive meetings lover	All	Commuting	-0.20	-5.32
Latent variable massive meetings lover	All	Shopping	-0.15	-4.69
Latent variable social meetings lover	Car	All	0.18	4.44
Latent variable social meetings lover	All	Commuting	-0.30	-7.04
Latent variable social meetings lover	All	Work-related	-0.38	-7.45
Latent variable social meetings lover	All	Education	-0.32	-6.55
Latent variable social meetings lover	All	Shopping	-0.19	-5.16
Latent variable high level of life satisfaction	All	Commuting	-0.18	-4.54
Latent variable high level of life satisfaction	All	Work-related	-0.15	-2.77
Latent variable high level of life satisfaction	All	Shopping	-0.14	-4.03
Latent variable concern towards PT	All	Commuting	0.17	4.24
Latent variable concern towards PT	All	Work-related	0.28	5.46
Latent variable concern towards PT	All	Education	0.27	5.31
Latent variable concern towards PT	All	Shopping	0.15	4.38
Wave B (1,0)	Car	All	-0.27	-2.50
Wave B (1,0)	PT	All	0.25	2.11
Wave B (1,0)	All	Shopping	-0.15	-2.04
Wave A (1,0)	All	Commuting	-0.51	-5.70
Wave A (1,0)	All	Work-related	-0.37	-3.09
Wave A (1,0)	All	Education	-0.60	-5.06
Wave A (1,0)	All	Shopping	-0.42	-4.91
Error component	Car	All	-0.49	-7.52
Error component	All	Commuting	-0.49	-7.25
Error component	All	Work-related	-0.88	-6.87
Error component	All	Education	-0.79	-6.61
Sample size	1951			
Number of parameters estimated	65			
Log-likelihood	-16,808.8			
AIC/n	17.298			

The satiation parameter estimates are presented in Table 9. Note that the satiation parameters account for the diminishing marginal utility associated with increased consumption of a good (that is to say that someone will eventually complete a number of trips for each purpose and/or mode that satisfies them). The generic α parameter was estimated as a function of α_{base} to ensure it lies between 0 and 1, as follows:

$$\alpha = \frac{1}{1+\exp^{-\alpha_{base}}} \quad (8)$$

The results for α_{base} show that $\alpha \to 0$, the utility function collapses to a linear expenditure system as presented in equation (7). The satiation effects of the γ parameters for each alternative (purpose *p* and mode *m*) are presented in Figure 5. These were simulated calculating the alternatives' deterministic utility value, V_{pm}, for each respondent in the sample (considering availability) and simulating the utility expression for different alternatives' number of trips values. Even though the location dummy variables for GSMA or SEQ were not significant themselves, there were differences across the statistically significant explanatory variables between them. Therefore, we can still analyse GSMA and SEQ separately as their baseline utilities and the average number of trips for each purpose-mode are different across waves given the model's explanatory variables.

Table 9. Model results MCDEV satiation parameters – mean (t-value)

Description	Mode	Purpose	Mean	T-value
α_{base}	All	All	-15.98	-0.21
γ	Car	Commuting	1.89	13.61
γ	PT	Commuting	2.09	8.33
γ	Active modes	Commuting	2.82	7.61
γ	Car	Work-related	2.10	10.10
γ	PT	Work-related	1.68	6.14
γ	Active modes	Work-related	1.31	5.72
γ	Car	Education	3.73	9.71
γ	PT	Education	1.62	5.70
γ	Active modes	Education	1.52	5.48
γ	Car	Shopping	0.70	15.12
γ	PT	Shopping	2.69	7.42
γ	Active modes	Shopping	1.87	9.88
γ	Car	Social/personal business	1.39	17.51
γ	PT	Social/personal business	2.11	8.03
γ	Active modes	Social/personal business	2.14	9.38

The results show that the satiation effect for commuting by car is the lowest, followed by shopping trips by car, by commuting by public transport, and then by personal business or social/recreation trips by car. That is, the benefit in the utility caused by one additional commuting or shopping trip by car is higher than for all other purpose-mode trips. For example, if a person is currently doing six one-way trips and decides to increase them by three, its accrued utility for commuting by car will increase by 0.95, it will increase by 0.72 for shopping by car, while it increases in approximately 1 point, and only 0.24 for shopping by public transport (dotted line). The highest satiation effects seem to be for education trips and work-related in active modes, followed by education and work-related trips in public transport, and then by work-related and education trips by car. These results show the importance of including purpose-specific satiation effects, which seem to be lowest for commuting and shopping trips, and highest for education and work-related trips; and mode-specific satiation effects, which are lowest for trips by car. The relationship between alternatives is equivalent between SEQ and GSMA, with the highest difference in commuting by car trips which has a significantly lower satiation effect in SEQ – suggesting that respondents in that area have a higher utility for doing one additional commuting trip by car.

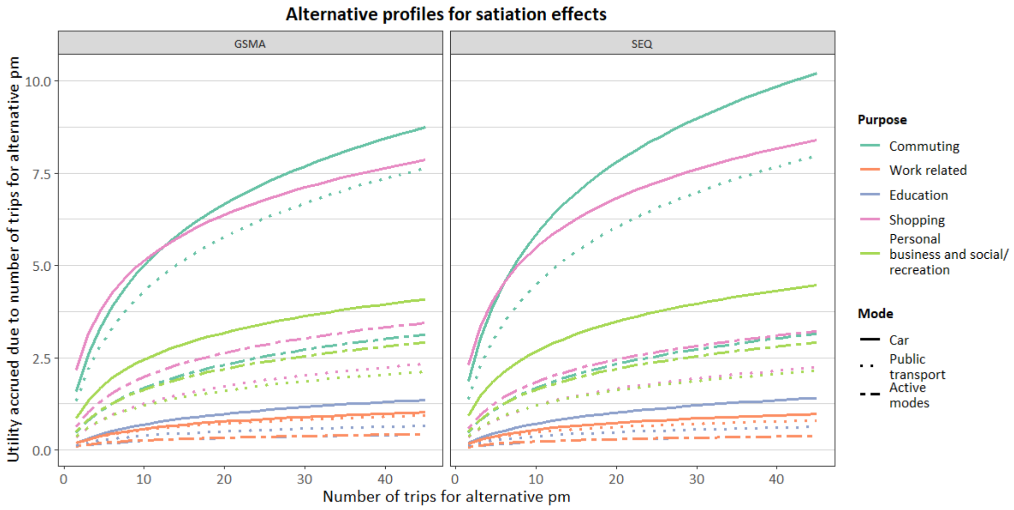

Figure 5. Alternative profiles' results for satiation effects

6. Simulated Scenarios

The simulation method for models was originally proposed by Pinjari & Bhat (2010). In this section, we calculate the optimal consumption for each alternative as follows (when $\alpha \to 0$):

$$x_{pm} = \left(\frac{\psi_{pm}}{\lambda} - 1\right)\gamma_{pm} \tag{9}$$

where $$\lambda = \frac{\sum_{p=1}^{P}\sum_{m=1}^{M}\gamma_{pm}\psi_{pm}}{B + \sum_{p=1}^{P}\sum_{m=1}^{M}\gamma_{pm}} \tag{10}$$

Scenarios were simulated by changing one of the explanatory variables and analysing the optimal consumption of number of one-way trips for each alternative. The first simulated scenario refers to the number of one-way trips by the proportion of days working from home, with the results presented in Figure 6. The results suggest that across all waves and jurisdictions, respondents that WFH more often are more likely to undertake shopping trips and personal business/social recreation trips, and less likely to make commuting trips. It is interesting to note that in SEQ in Wave C, the increment in shopping trips seems to be higher as the frequency of WFH increases compared to other waves.

The second simulated scenario represents the changes in the number of one-way trips given by the distance from home to work, which are presented in Figure 7. This explanatory variable does not have the same significant influence as the proportion of days WFH. However, it shows a slight increase in commuting trips by car (continuous dark green line) and a decrease in the number of commuting trips by public transport (dotted dark green line) – with a similar relationship in the case of the shopping and work-related trips.

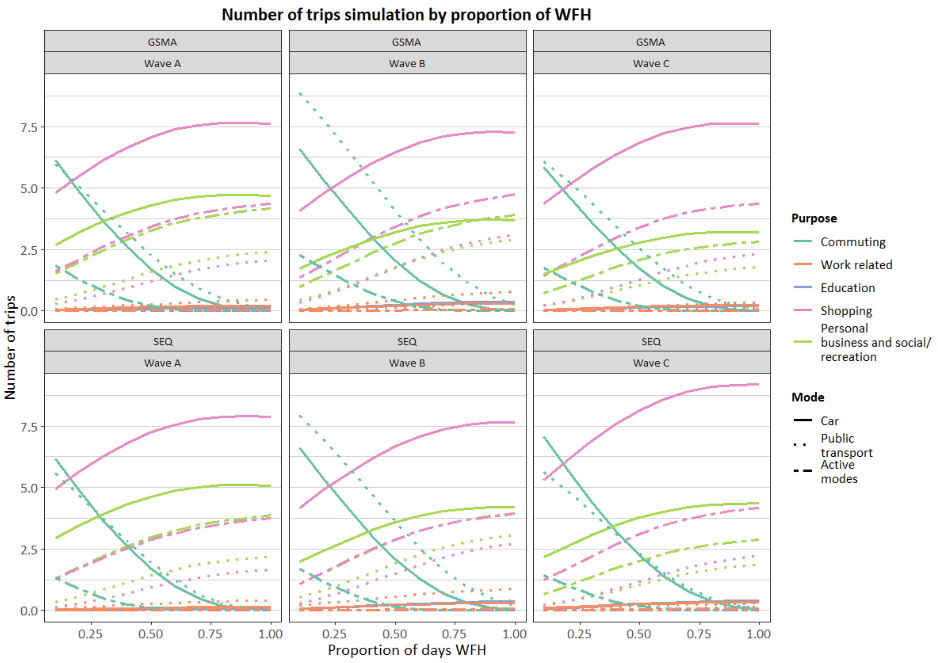

Figure 6: Simulated number of one-way trips by proportion of WFH

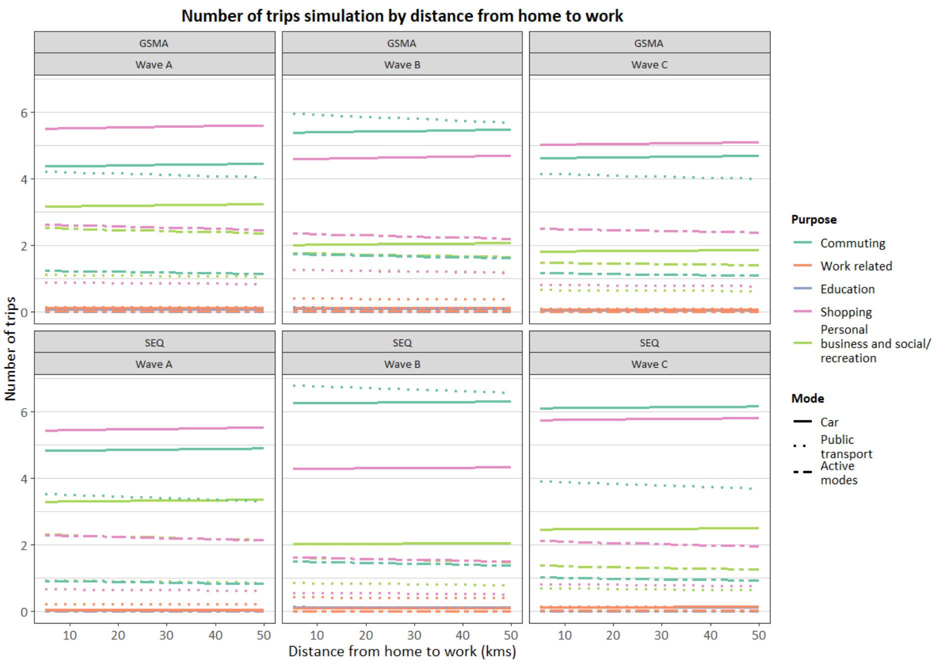

Figure 7: Simulated number of one-way trips by distance from home to work

We also simulated scenarios for the latent variables. It is important to note, however, that the value of the latent variable does not have a direct value as they are calculated using factor analysis. The average of the latent variables across the sample are close to zero, and the value for each respondent shows how likely they are to belong to each category. For example, a respondent that has the highest value for life satisfaction represents a participant that was on the higher end of life satisfaction relative to the other participants. The results for life satisfaction latent variable are presented in Figure 8. These results show that participants that feel more satisfied with their life in general today undertake less commuting and shopping trips and seem to be undertaking more personal business/social recreation trips. In Wave A, the positive influence on personal business/social recreation trips was higher than in Wave B and C; but in SEQ it seemed to increase in Wave C relative to B. The simulated scenario for the latent variable that represents the level of comfort going to social meetings is presented in Figure 9. Respondents that are more comfortable attending social meetings are less likely to undertake commuting trips, with the negative influence higher for commuting trips by public transport than other modes. Similarly, the level of comfort associated with attending social meetings has a positive influence on shopping trips made by car but a negative influence on shopping trips by public transport. As expected, it has a positive influence on the number of personal business/social recreation trips, and its influence is higher for trips made by car than other modes.

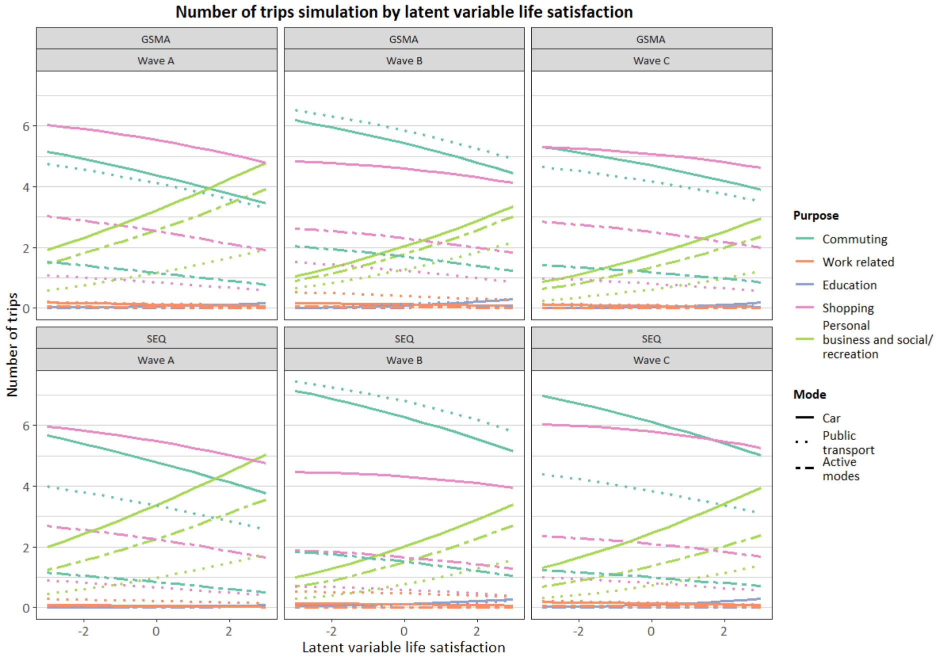

Figure 8: Simulated number of one-way trips by the latent variable for life satisfaction

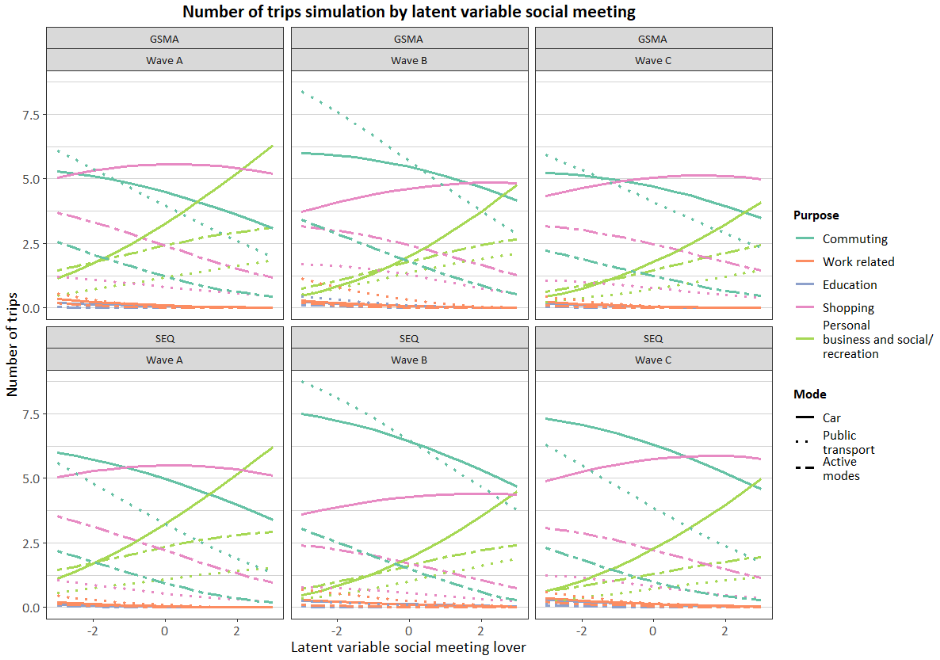

Figure 9: Simulated number of one-way trips by the latent factor for social meeting lover

The simulated scenarios for the latent variable representing concern about the use of public transport is summarised in Figure 10. Interestingly, the results show that respondents that are more concerned about the use of public transport seem to have a similar view on the number of trips made by car and public transport (i.e., slopes for each purpose type are similar). The results suggest that individuals who are more concerned about the use of public transport are more likely to undertake commuting trips by all modes, are more likely to undertake shopping trips, and less likely to make personal business/social recreation trips. As mentioned above, respondents that are more concerned about contact with other individuals through the use of public transport, will probably avoid doing non-essential trips and only focus on going to work and food shopping.

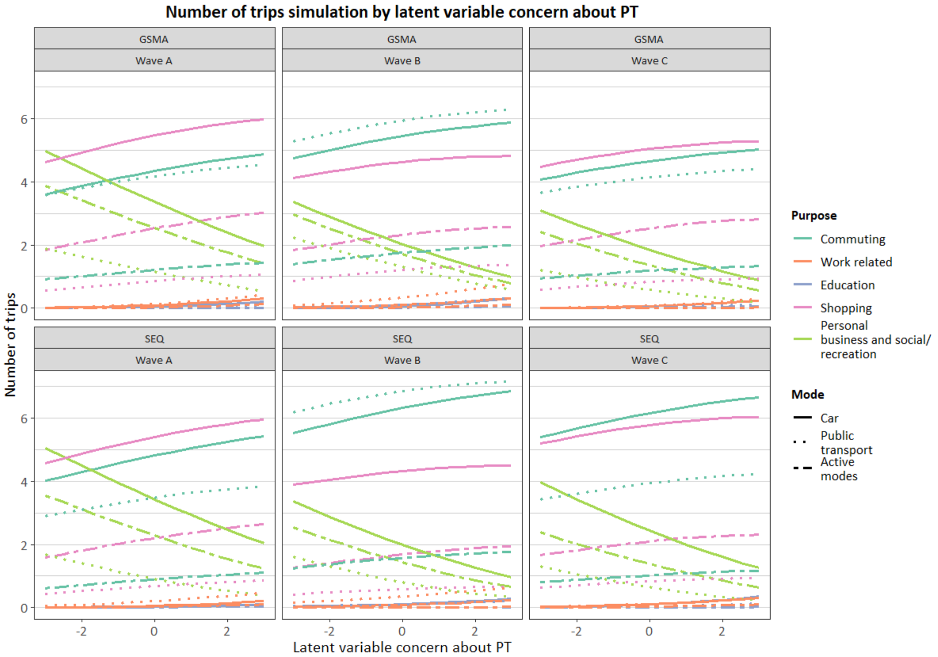

Figure 10: Simulated number of one-way trips by the latent variable for public transport use concern

7. Conclusions

This paper investigated the influence of working from home and other explanatory variables on the number of weekly one-way trips made by workers in two metropolitan regions in GSMA and SEQ. A multiple discrete-continuous extreme value (MDCEV) model was estimated to provide a behavioural understanding of the number of one-way trips undertaken by different purposes and modes at three points in time during the pandemic. Fifteen alternatives were considered in total, each representing a combination of five purposes (i.e., commuting, work-related, education, shopping, personal business/social recreation trips) and three modes of transport (i.e., car, public transport and active modes). The results showed a correlation between the alternatives that represented trips made by car, alternatives representing commuting, work-related and education trips by any mode. The estimated parameters that refer to satiation effects show statistically significant differences between purposes and modes, being the lowest for commuting and shopping trips, and highest for education and work-related trips; and for mode-specific satiation effects, they are lowest for trips by car. The wave dummy variables suggest that participants in Wave A were less likely to do all but social recreation/personal business trips relative to Wave C; and in Wave B respondents less likely to undertake commuting or shopping trips and more likely to use public transport relative to

Wave C. These findings suggest that during the first year of the pandemic respondents were working from home more often and avoided any trips that were not related to their social life or personal business – which are associated to trips with no or little contact with strangers. Right before one of the longest lockdowns in Australia – where COVID-19 cases had significantly increased in the country, respondents chose to WFH when possible, and avoided trips in which they will probably have contact with different people, such as shopping or public transport trips.

Scenarios were simulated to obtain an understanding of how the model estimates can be used to establish the behavioural implications of changing levels of relevant explanatory variables on the changes in one-way trips by purpose and mode. Given a specific interest in the role of increased WFH, the simulation results suggest across all waves and jurisdictions, that individuals who WFH more often are more likely to undertake increased shopping trips and personal business/social recreation trips, and less likely to undertake commuting trips, the latter expected. The latent variable for life satisfaction suggests that respondents who are more satisfied with their life nowadays are less likely to undertake commuting and shopping trip, but more likely to undertake more personal business/social recreation trips. In Wave A, the positive influences on personal business/social recreation trips were greater than in Waves B and C; however in SEQ this seemed to increase in Wave C relative to B. Interestingly, the latent variable for concern towards the use of public transport has a similar influence on the number of one-way trips made by car and public transport, with individuals more likely to undertake commuting trips by all modes, more likely to make more shopping trips, and less likely to undertake personal business/social recreation trips.

While there has been a significant amount of research on how the COVID-19 pandemic has impacted on the incidence of commuting activity, especially by mode, in large measure due to increased working from home, the translation of this impact to all trip purposes and modes has been somewhat neglected. Given a finite amount of weekly time available, it is useful to know the extent to which increased WFH and consequent reduced commuting trips has resulted in changes in the incidence of travel by other trip purposes and associated modes. Prior to the pandemic there has been limited attempt to examine the relationship between WFH and other trip making behaviour; some literature finding it to be a complement for non-commuting trips (Mokhtarian et al., 1995, 2004; Choo et al., 2005) and others finding reduced commuting trips being substituted for non-commuting trips (Zhu, 2012; Kim et al., 2015). In this study, we find that those who WFH at a higher rate also have relatively more non-commuting trip activity. This is likely to have spatial implications as this non-commuting activity is likely to be occurring in more local suburban areas in and around the homes where those WFH live. Although not detailed specifically in this paper, we are seeing strong signs that this 'next normal' is almost certainly resulting in a longer-term growth in local trips for all trip purposes with modal substitution occurring between car, public transport and active modes (the latter growing fast in terms of walking, bicycles and e-scooters).

We consistently find the satiation parameter for cars to be lower than that for other modes across all time periods, meaning that car use will likely grow more quickly and to higher levels than other modes. This is borne out both in the GSMA and SEQ where vehicle use has rebounded very strongly in both areas, often exceeding levels observed prior to the start of the pandemic. This suggests that the dominance of the private vehicle as the preferred mode for trip making has been strengthened by the pandemic and if use of the car is to be reduced, there will likely need to be an external policy measure to dampen “consumption”. Finally, we also observe strong rebounds in social activity when confidence returns about meeting safely with family and friends, particularly in small group and/or lower risk social contexts. Beck et al. (2022) flagged a potential for pandemic fatigue becoming a significant concern when mixed with a growing desire to engaging in day-to-day activities where comfort in completing those activities was returning, arguing that authorities would need to communicate the need for caution and observance of COVID-19 health protocols, or else the potential for contagion would be high. Unfortunately, in Sydney as an example, as social trip making and connections rebounded heavily, rates of transmission grew exponentially, ultimately forcing the city into an extended lockdown. Moving forward, potentially into other pandemic situations should they arise, it will again be the strong rebound in social activity that will likely cause contagion – as social activity is a key part of the human condition. Lastly, we find a strong link between rates of WFH and measures of wellbeing (Hensher & Beck, 2022). Admittedly, if you are able to WFH well, you are likely to be more positive about your life compared to those who have been unable to do so, but similarly in ongoing work we find that the ability to WFH provides those who can the opportunity to use time more flexibly such that not only do their employers benefit, but their work-life balance is improved. Such balance between WFH and work in the office should be a key component of work moving forward given the win-win for business and society.

By identifying some of the key influences on patterns of change in mobility, we anticipate gaining an improved behavioural understanding on the switching patterns of travel. An appropriate behavioural modelling framework to achieve this is one that can account for the choice of mode (a discrete decision) and the frequency of one-way trips (a continuous choice) by trip purpose, recognising the presence of budget constraints and satiation effects. The MCDEV model framework enables us to assess the changes in mobility patterns in a behavioural appealing way. The evidence found in the analysis of trip making changes between three periods during the ongoing pandemic suggests that increased WFH and reduced commuting is associated with varying rates of change in one-way non-commuting trip making behaviour which varies by trip purpose and mode. Failure to recognise this behavioural response across all trip-making activity, if the focus is only on commuting changes, will result in misinformed advice on how the pandemic has changed the overall amount of travel activity. Figure 6 in particular shows how WFH impacts on the incidence of one-way trips by trip purpose and mode, which are, on average, significant changes.

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Declarations of interest: none.

References

Astroza, S., Tirachini, A., Hurtubia, R., Carrasco, J. A., Guevara, A., Munizaga, M., Figueroa, M., & Torres, V. (2020). Mobility Changes, Teleworking, and Remote Communication during the COVID-19 Pandemic in Chile. *Findings*, *1*(Ine 2018), 1–8. https://doi.org/10.32866/001c.13489

Balbontin, C., Hensher, D. A., & Beck, M. J. (2022). Relationship between commuting and non-commuting travel activity under the growing incidence of working from home and people's attitudes towards COVID-19. *Transportation (under Review)*.

Balbontin, C., Hensher, D. A., Beck, M. J., Giesen, R., Basnak, P., Vallejo-Borda, J. A., & Venter, C. (2021). Impact of COVID-19 on the number of days working from home and commuting travel: A cross-cultural comparison between Australia, South America and South Africa. *Journal of Transport Geography*, 103188. https://doi.org/10.1016/j.jtrangeo.2021.103188

Barbieri, D. M., Lou, B., Passavanti, M., Hui, C., Hoff, I., Lessa, D. A., Sikka, G., Chang, K., Gupta, A., Fang, K., Banerjee, A., Maharaj, B., Lam, L., Ghasemi, N., Naik, B., Wang, F., Mirhosseini, A. F., Naseri, S., Liu, Z., … Rashidi, T. H. (2021). Impact of COVID-19 pandemic on mobility in ten countries and associated perceived risk for all transport modes. *PLoS ONE*, *16*(2 February), 1–18. https://doi.org/10.1371/journal.pone.0245886

Bartlett, M. S. (1951). The Effect of Standardization on a χ 2 Approximation in Factor Analysis. *Biometrika*, *38*(3/4), 337. https://doi.org/10.2307/2332580

Beck, M. J., & Hensher, D. A. (2020). Insights into the impact of COVID-19 on household travel and activities in Australia – The early days of easing restrictions. *Transport Policy*, *99*, 95–119. https://doi.org/10.1016/j.tranpol.2020.08.004

Beck, M. J., Hensher, D. A., & Wei, E. (2020). Slowly coming out of COVID-19 restrictions in Australia: Implications for working from home and commuting trips by car and public transport. *Journal of Transport Geography*, *88*, 102846. https://doi.org/10.1016/j.jtrangeo.2020.102846

Beck, M. J., Nelson, J. D., & Hensher, D. A. (2022). Attitudes Towards Public Transport post Delta COVID-19 Lockdowns: Identifying User Segments and Policies to Restore Confidence. *International Journal of Sustainable Transportation (under Review)*.

Bhaduri, E., Manoj, B. S., Wadud, Z., Goswami, A. K., & Choudhury, C. F. (2020). Modelling the effects of COVID-19 on travel mode choice behaviour in India. *Transportation Research Interdisciplinary Perspectives*, *8*(November), 100273. https://doi.org/10.1016/j.trip.2020.100273

Bhat, C. R. (2005). A multiple discrete-continuous extreme value model: Formulation and application to discretionary time-use decisions. *Transportation Research Part B: Methodological*, *39*(8), 679–707. https://doi.org/10.1016/j.trb.2004.08.003

Bhat, C. R. (2008). The multiple discrete-continuous extreme value (MDCEV) model: Role of utility function parameters, identification considerations, and model extensions. *Transportation Research Part B: Methodological*, *42*(3), 274–303. https://doi.org/10.1016/j.trb.2007.06.002

Bhat, C. R., Astroza, S., & Bhat, A. C. (2016). On allowing a general form for unobserved heterogeneity in the multiple discrete-continuous probit model: Formulation and application to tourism travel. *Transportation Research Part B: Methodological*, *86*, 223–249. https://doi.org/10.1016/j.trb.2016.01.012

Calastri, C., Hess, S., Daly, A., Maness, M., Kowald, M., & Axhausen, K. (2017). Modelling contact mode and frequency of interactions with social network members using the multiple discrete–continuous extreme value model. *Transportation Research Part C: Emerging Technologies*, *76*, 16–34. https://doi.org/10.1016/j.trc.2016.12.012

Choo, S., Mokhtarian, P. L., & Salomon, I. (2005). Does telecommuting reduce vehicle-miles traveled? An aggregate time series analysis for the U.S. *Transportation*, *32*(1), 37–64. https://doi.org/10.1007/s11116-004-3046-7

Fatmi, M. R. (2020). COVID-19 impact on urban mobility. *Journal of Urban Management*, *9*(3), 270–275. https://doi.org/10.1016/j.jum.2020.08.002

Hensher, D. A., & Beck, M. J. (2022). Exploring the link between working from home and how worthwhile the things that you do in life are during COVID-19. *Transport Policy (under Review)*.

Hensher, D. A., Wei, E., Beck, M. J., & Balbontin, C. (2021a). The impact of COVID-19 on cost outlays for car and public transport commuting - The case of the Greater Sydney Metropolitan Area after three months of restrictions. *Transport Policy*, *101*(September 2020), 71–80. https://doi.org/10.1016/j.tranpol.2020.12.003

Hensher, D. A., Wei, E., Beck, M. J., & Balbontin, C. (2021b). The impact of COVID-19 on cost outlays for car and public transport commuting - The case of the Greater Sydney Metropolitan Area after three months of restrictions. *Transport Policy*, *101*, 71–80. https://doi.org/10.1016/j.tranpol.2020.12.003

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*. https://doi.org/10.1007/BF02289447

Jiao, J., & Azimian, A. (2021). Exploring the factors affecting travel behaviors during the second phase of the COVID-19 pandemic in the United States. *Transportation Letters*, *13*(5–6), 331–343. https://doi.org/10.1080/19427867.2021.1904736

Jokubauskaitė, S., Hössinger, R., Aschauer, F., Gerike, R., Jara-Díaz, S., Peer, S., Schmid, B., Axhausen, K. W., & Leisch, F. (2019). Advanced continuous-discrete model for joint time-use expenditure and mode choice estimation. *Transportation Research Part B: Methodological*, *129*, 397–421. https://doi.org/10.1016/j.trb.2019.09.010

Kaiser, H. F., & Rice, J. (1974). Little Jiffy, Mark Iv. *Educational and Psychological Measurement*, *34*(1), 111–117. https://doi.org/10.1177/001316447403400115

Kim, S. N., Choo, S., & Mokhtarian, P. L. (2015). Home-based telecommuting and intra-household interactions in work and non-work travel: A seemingly unrelated censored regression approach. *Transportation Research Part A: Policy and Practice*, *80*, 197–214. https://doi.org/10.1016/j.tra.2015.07.018

Mokhtarian, P. L., Collantes, G. O., & Gertz, C. (2004). Telecommuting, Residential Location, and Commute-Distance Traveled: Evidence from State of California Employees. *Environment and Planning A: Economy and Space*, *36*(10), 1877–1897. https://doi.org/10.1068/a36218

Mokhtarian, P. L., Handy, S., & Salomon, I. (1995). Methodological Issues in the Estimation of the Travel, Energy, and Air Quality Impacts of Telecommuting. *Transportation Research Record A*, *29A*(4), 283–302. https://escholarship.org/uc/item/44n3k2jp

Palma, D., Enam, A., Hess, S., Calastri, C., & Crastes dit Sourd, R. (2021). Modelling multiple occurrences of activities during a day: an extension of the MDCEV model. *Transportmetrica B*, *9*(1), 456–478. https://doi.org/10.1080/21680566.2021.1900755

Pinjari, A. R., & Bhat, C. (2010a). A multiple discrete-continuous nested extreme value (MDCNEV) model: Formulation and application to non-worker activity time-use and timing behavior on weekdays. *Transportation Research Part B: Methodological*, *44*(4), 562–583. https://doi.org/10.1016/j.trb.2009.08.001

Pinjari, A. R., & Bhat, C. (2010b). An Efficient Forecasting Procedure for Kuhn-Tucker Consumer Demand Model Systems. *Technical Paper*, *Department of Civil & Environmental Engineering*, *University of South Florida*. http://www.ce.utexas.edu/prof/bhat/ABSTRACTS/Pinjari_Bhat_MDCEV_Forecasting_June14_RES.pdf

Pinjari, A. R., Bhat, C. R., & Hensher, D. A. (2009). Residential self-selection effects in an activity time-use behavior model. *Transportation Research Part B: Methodological*, *43*(7), 729–748. https://doi.org/10.1016/j.trb.2009.02.002

Politis, I., Georgiadis, G., Papadopoulos, E., Fyrogenis, I., Nikolaidou, A., Kopsacheilis, A., Sdoukopoulos, A., & Verani, E. (2021). COVID-19 lockdown measures and travel behavior: The case of Thessaloniki, Greece. *Transportation Research Interdisciplinary Perspectives*, *10*(March), 100345. https://doi.org/10.1016/j.trip.2021.100345

Vallejo-Borda, J. A., Giesen, R., Mella Lira, B., Basnak, P., Reyes, J. P., Ortúzar, J. de D., Hensher, D. A., & Beck, M. J. (2022). Characterising public transport shifting to active and private modes in South American capitals during the Covid-19 pandemic. *Transportation Research Part A: Policy and Practice (under Review)*, *Special Issue on COVID-19 (edited by Hani Mahmassani and Patricia Mokhtarian).*

Zhang, J., Hayashi, Y., & Frank, L. D. (2021). COVID-19 and transport: Findings from a world-wide expert survey. *Transport Policy*, *103*(December 2020), 68–85. https://doi.org/10.1016/j.tranpol.2021.01.011

Zhu, P. (2012). Are telecommuting and personal travel complements or substitutes? *Annals of Regional Science*, *48*(2), 619–639. https://doi.org/10.1007/s00168-011-0460-6

Appendix

Table 10: Percentage of respondents that do at least one trip for each purpose-mode and the number of trips they do by state and wave

	Wave A				Wave B				Wave C			
	GSMA		SEQ		GSMA		SEQ		GSMA		SEQ	
	%	N Trips	%	N Trips	%	N Trips	%	N Trips	%	N Trips	%	N Trips
Commute by car	49%	5.97 (4.22)	51%	6.21 (3.42)	60%	6.01 (3.49)	70%	6.89 (4.68)	45%	5.99 (3.94)	59%	6.47 (3.69)
Commute by public transport	13%	5.73 (4.31)	12%	5.24 (3.71)	16%	3.98 (2.72)	15%	4.80 (3.15)	20%	5.94 (3.91)	15%	5.76 (3.08)
Commute by active modes	11%	4.71 (4.42)	10%	4.38 (3.05)	13%	3.76 (2.98)	7%	4.29 (3.59)	8%	5.22 (3.54)	8%	4.97 (3.20)
Work-related trips by car	20%	3.99 (6.34)	21%	3.45 (3.25)	23%	4.01 (6.75)	18%	4.22 (3.96)	15%	3.45 (2.89)	23%	5.01 (7.01)
Work-related trips by public transport	6%	5.60 (11.65)	4%	3.54 (2.67)	11%	3.50 (2.68)	4%	4.25 (2.34)	5%	3.27 (2.15)	4%	2.77 (2.49)
Work-related trips by active modes	5%	3.10 (2.94)	4%	3.85 (4.43)	8%	1.39 (0.69)	4%	1.82 (1.60)	3%	2.44 (1.01)	3%	6.55 (7.43)
Education trips by car	16%	4.34 (3.14)	19%	5.76 (3.65)	23%	4.04 (3.12)	19%	5.37 (4.40)	18%	4.40 (3.05)	24%	6.16 (4.23)
Education trips by public transport	3%	2.92 (2.07)	3%	2.82 (1.89)	8%	3.48 (2.50)	4%	2.67 (1.15)	4%	2.15 (1.72)	3%	2.91 (1.51)
Education trips by active modes	5%	4.60 (4.04)	4%	3.00 (2.70)	8%	1.57 (1.29)	4%	2.67 (3.03)	2%	4.14 (2.85)	2%	2.17 (0.98)
Shopping trips by car	70%	4.55 (4.80)	79%	4.15 (3.92)	77%	4.33 (3.49)	76%	3.81 (3.50)	61%	4.19 (2.86)	79%	4.70 (3.47)
Shopping trips by public transport	7%	4.32 (3.19)	8%	3.52 (2.53)	12%	4.84 (2.83)	5%	4.88 (2.36)	9%	2.73 (2.60)	6%	5.00 (2.93)
Shopping trips by active modes	22%	4.03 (3.28)	17%	3.62 (3.18)	19%	3.68 (3.85)	8%	2.96 (2.64)	17%	4.07 (2.91)	8%	3.67 (2.83)
Social recreation/personal business trips by car	56%	4.17 (4.77)	60%	3.82 (2.51)	56%	3.26 (2.28)	55%	3.54 (3.30)	41%	3.31 (2.42)	53%	3.96 (3.14)
Social recreation/personal business trips by public transport	8%	2.61 (1.98)	9%	2.87 (2.10)	13%	4.77 (3.17)	6%	4.95 (3.36)	11%	2.72 (2.33)	6%	3.82 (2.59)
Social recreation/personal business trips by active modes	18%	5.00 (4.83)	16%	4.94 (4.61)	17%	3.36 (2.57)	7%	3.24 (1.79)	13%	4.53 (3.81)	8%	4.11 (3.10)