RELATIONSHIP BETWEEN COMMUTING AND NON-COMMUTING TRAVEL ACTIVITY UNDER THE GROWING INCIDENCE OF WORKING FROM HOME AND PEOPLE'S ATTITUDES TOWARDS COVID-19

Camila Balbontin
David A. Hensher
Matthew J. Beck
Institute of Transport and Logistics Studies (ITLS), The University of Sydney Business School
Camila.Balbontin@sydney.edu.au
David.Hensher@sydney.edu.au
Matthew.Beck@sydney.edu.au

ABSTRACT

After a year or more since the pandemic spread throughout the world, working for home (WFH) is becoming a more popular and legitimate alternative to choosing a commuting mode. With WFH continuing, non-commuting travel is also likely to change as workers and their families have greater flexibility in when and to what extent they conduct their shopping, social-recreation and other non-commuting trip activity. This paper recognises that all trip purpose activity is being impacted by the pandemic and that the drivers of the number of trips by each and every trip purpose need to be identified as a way of establishing likely future levels of frequency of all trip making.

Keywords: COVID-19; commuting trips; non-commuting trips; work from home

1 INTRODUCTION

COVID-19 has had a significant impact on how countries operate in various settings. In relation to work, there has been a substantial increase in working from home (WFH), which has had a range of impacts on people's lives. While travel to and from the workplace has been affected by the pandemic, so has travel for other purposes (for example, going to the supermarket or to the doctor). As part of a larger study focused on revisions to strategic transport models to accommodate WFH as a growing alternative to commuting mode choice (Hensher, Beck, et al., 2021; Hensher, Balbontin, et al., 2021), we need to recognise that changes in commuting activity as a result of increased WFH will also have an impact on the amount of non-commuting travel activity. With WFH changing the hours that many people actually work, including staggered working hours where commuting to the office occurs, the entire seven days of the week and weekend become candidate times for travel that pre-COVID-19 would have been more constrained as workers commuted five days a week and typically worked a 9 to 5 day, with variations around this common time slice.

This paper focuses on developing a series of models that use data collected during late 2020 in Australia (New South Wales and Queensland) in order to understand the relationship between working from home, perceptions about COVID-19, and one-way weekly trips for six trip purposes for both working and non-working people (unemployed or retired). Other studies on the impact of COVID-19 in Australia have focused on commuting (Beck & Hensher, 2020; Beck et al., 2020; Hensher et al., 2021).

For each trip purpose, a Poisson regression model is estimated, in which the dependent variable is the number of one-way weekly trips, a count variable. The candidate explanatory variables include sociodemographic characteristics of the participants (i.e., age, income, gender, profession), residential and work location (i.e., regional / suburban dummy variables), proportion of days worked from home relative to total days worked in the last week, and variables that represent the perception of COVID-19. For the latter, factor analysis is undertaken to combine responses to attitudinal questions that refer to the concern for COVID-19 in the life of each person and their community, the response of the authorities, and how comfortable they feel using public transport. An important objective of this study is to identify what are the systematic drivers influencing commuting and non-commuting travel behaviour for workers, non-workers and users in both regional and metropolitan areas during COVID-19, where working from home and bio-security concerns more generally are having a noticeable impact on travel behaviour.

The paper is organised as follows. The next section provides a brief background of other studies that have looked at the effects of COVID-19 on travel behaviour. Section 3 describes the data used in this study, followed by the methodology used. Section 5 presents the model results as well as a number of interesting mean direct elasticities. The next section presents simulated scenarios to analyse the level of sensitivity of the one-way weekly trips by purpose type; and the last section summarises the main findings.

2 BACKGROUND

Since early 2020 when the COVID-19 pandemic spread across the world, many organisations and individuals have embarked on research designed to gain a better understanding of the impact

that COVID-19 has had on the way we gave about our daily activities. The interest herein is on understanding the impact of COVID-19 travel behaviour, with the growth in working for home as an alternative to commuting in particular. Hensher, Beck, & Wei (2021) collected data in early 2020 in Australia to understand the number of one-way commuting trips by car and public transport in Australia given the disruptions caused by COVID-19. Their findings suggest that the increase in WFH has had a major impact on travel behaviour and needs to be embedded in future revisions of strategic transport model systems. Beck & Hensher (2020) analyse the implications on travel behaviour in Australia by mid-2020. Their findings suggest that by mid-2020, travel activity had started to slowly return to normal in Australia, in particular by private car and for trips related to shopping and social/recreation. However, work from home prevailed and respondents had a positive opinion towards it. Beck et al. (2020) look at WFH in more detail, finding that the role of the employer is very important and determines how many days people are working from home. They also find that WFH is generally higher in metropolitan areas and households with higher income levels, which is probably related to the nature of employment.

Hensher, Balbontin, Beck, & Wei (2021) formalise the relationship between WFH and commuting by day of the week and time of day using data collected in late 2020 in Australia. They use a mixed logit choice model to identify the influence of different explanatory variables such as income, age, concern about the use of public transport, among others, in the choice to WFH or to commute by different modes and at different times of the day. Their very high aggregate level results show that the adjustments of WFH should be around 0.3 and 0.4 representing the probability to WFH relative to commuting in any mode of transport (i.e., between 30 to 40% of workers WFH everyday).

Zhang, Hayashi, & Frank (2021) undertook a worldwide expert survey during the early stages of COVID-19 to understand the effect on travel. Their findings confirm that public transport usage decreased significantly, and most of the modal shift was to active transport followed by car, especially in Europe. Balbontin et al. (2021) compare travel behaviour in different countries around the world but using an online panel survey in Australia, South Africa and different countries in South America. Their results suggest a dramatic decrease in the use of public transport, but most of the participants had moved to private car, followed by active modes (bicycle and walk). Their results indicated a high incidence of WFH, either mandatory or by choice. Barbieri et al. (2021) study individual mobility patterns for all transport modes in ten countries on six continents. Their results show a substantial reduction in the frequency of commuting and non-commuting trips in all modes. The authors study the risk perception of using different modes of transport using three Likert-type queries. Their results suggest that socio-economic inequality and morbidity are related to health risks and also to perceived risks.

The Australian evidence aligns well with a recent USA study by Barrero, Bloom, & Davis (2021) who surveyed more than 30,000 USA residents over multiple waves in 2020 to investigate whether WFH will stick, and why. They found that 20 percent of full workdays will be supplied from home after the pandemic ends, compared with just 5 percent before, of which 2 days a week is not uncommon. They provide five reasons for this large shift: better-than-expected WFH experiences, new investments in physical and human capital that enable WFH, greatly diminished stigma associated with WFH, lingering concerns about crowds and contagion risks, and a pandemic-driven surge in technological innovations that support WFH. The consequences are that employees will enjoy large benefits from greater remote work, especially those with higher earnings; the shift to WFH will directly reduce spending in major city centres by at least 5-10 percent relative to the pre-

pandemic situation; data on employer plans and the relative productivity of WFH imply a 5 percent productivity boost in the post-pandemic economy due to re-optimized working arrangements; and only one-fifth of this productivity gain will show up in conventional productivity measures, because they do not capture the time savings from less commuting. Contrasts with developing economies have been studied in Balbontin et al. (2021) who investigated the relationship between WFH and commuting activity in South Africa, and five South American capital cities (i.e., Buenos Aires, Bogotá, Lima, Quito and Santiago) in August-December 2020, using questions derived from the Australian study. The number of days working from home has more variation across countries, where the lowest is in Australia with 1.63 average days WFH, followed by South Africa with 2.31 days; and the highest is Argentina with 3.43 days WFH followed by Chile with 3.19 days.

There is still much more to be done on the longer-term impacts of COVID-19 on travel behaviour. To the best of our knowledge, this is the first study that analyses the implications of COVID-19, from a WFH perspective but also from an attitudes and perceptions perspective, for both commuting and non-commuting travel behaviour, including workers, non-workers, metropolitan and regional areas.

3 DATA DESCRIPTION

The data used in this study was collected through an online survey in two states in Australia: New South Wales (NSW) and Queensland (QLD), in late 2020. The survey included questions on employment status, socio-demographics, work from home experience, travel behaviour, and attitudinal questions towards working from home, COVID-19, community and government response, among others. This paper focuses on understanding the effect of COVID-19 on respondents' travel behaviour for people currently employed and not employed. Six different purpose types are considered in this study: (1) commuting trips; (2) work-related trips; (3) education/childcare trips; (4) shopping trips (i.e., food and general shopping); (5) personal business trips; and (6) social recreation trips. The commuting and work-related trips are only valid when a respondent is currently employed, referred to as workers; otherwise, he/she is a non-worker. The analysis includes respondents that live in metropolitan areas – namely, in the Greater Sydney Metropolitan Area (GSMA) in NSW[1], and in Southeast Queensland (SEQ[2]) in QLD – and respondents that live in regional areas in both NSW and QLD[3]. Figure 1 profiles the average number of one-way weekly trips by purpose type and employment status in the metropolitan and regional areas of NSW and QLD.

The majority of one-way weekly trips are commuting trips; they are higher in regional areas where we have observed far less days WFH. The second highest average number of trips is for shopping, followed by social/recreation activity. The number of trips with an education/childcare purpose is significantly lower for non-workers compared to workers in regional areas; the same relationship is true in metropolitan areas but the difference between workers and non-workers is small. The average number of personal business trips and social/recreation trips in regional areas are greater

[1] This includes, Sydney, Newcastle, Wollongong/Illawarra, Central Coast,

[2] This includes Brisbane, the Sunshine Coast and the Gold Coast.

[3] The regional areas in Queensland are Townsville, Cairns Toowoomba, Bundaberg, Gladstone, Mackay and Rockhampton. In NSW the regional Centres included are Wagga Wagga, Port Macquarie, Coffs Harbour, Tamworth, Armidale, Orange, Bathurst, Dubbo, Parkes and a number of smaller locations.

for non-workers, but in metropolitan areas they are higher for workers. The average number of shopping trips is slightly higher for non-workers in metropolitan areas, and almost the same in regional areas, compared to workers. The average for personal business trips is higher for workers relative to non-workers in all areas except regional NSW. A summary of the non-attribute variables investigated as sources of variation on trip purposes are summarised in Table 1. As expected, income is significantly lower for non-workers than workers, while age is also higher for non-workers than workers. The proportion of days worked from home in a 7-day week is significantly higher in metropolitan areas (0.35) than in regional areas (0.14).

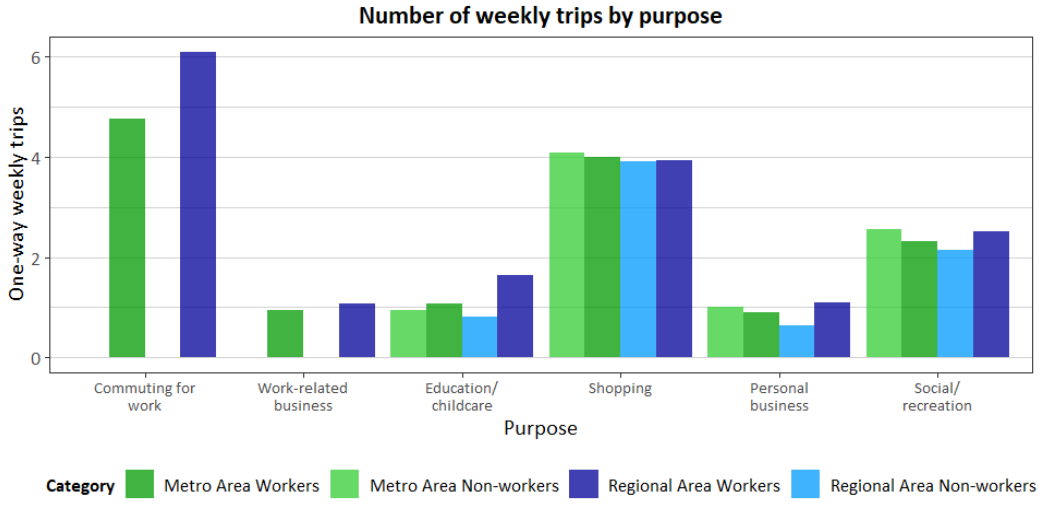

Figure 1: Average number of weekly trips by purpose in September 2020

Table 1: General descriptive statistics – mean (standard deviation)

	Metropolitan Area		Regional Area	
	Non-workers	**Workers**	**Non-workers**	**Workers**
Age (years)	58.62 (17.04)	40.15 (13.42)	57.27 (17.14)	38.62 (13.48)
Gender female (0,1)	62%	64%	62%	68%
Number of adults in household	1.57 (0.75)	1.68 (1.01)	1.58 (0.85)	1.66 (0.98)
Number of cars in household	1.30 (0.77)	1.64 (0.94)	1.59 (1.14)	2.05 (1.02)
Number of children in household	0.75 (1.17)	1.11 (1.35)	0.90 (1.36)	1.18 (1.48)
At least one child in primary school (0,1)	-	22%	-	23%
Personal income ('000AUD$)	35.68 (32.63)	78.14 (51.03)	32.42 (27.58)	67.31 (46.31)
Proportion of days WFH	-	0.35 (0.43)	-	0.14 (0.30)
Number of days WFH	-	1.66 (2.12)	-	0.61 (1.40)
Distance from home to office (kms)	-	19.48 (32.47)	-	18.38 (28.66)
Used car to go to work last week (0,1)	-	69%	-	93%
Used train/light rail to go to work last week (0,1)	-	12%	-	-
Used bus to go to work last week (0,1)	-	6%	-	1%
Prior to COVID-19 used car to go to work (0,1)	-	63%	-	93%
Prior to COVID-19 used train/light rail to go to work (0,1)	-	20%	-	-
Prior to COVID-19 used bus to go to work (0,1)	-	9%	-	2%
Brisbane (0,1)	18%	21%	-	-

	Metropolitan Area		Regional Area	
Central Coast (0,1)	12%	7%	-	-
Located in the state of NSW (0,1)	64%	62%	76%	30%
Located in the state of QLD (0,1)	36%	38%	24%	70%
Number of observations	269	627	141	311

4 METHODOLOGY

The purpose of this study is to understand how the number of one-way trips for different purposes are affected by the COVID-19 pandemic. The proportion of work being done from home is an observable variable that is directly related to COVID-19. However, there are other underlying attitudes towards COVID-19 that might be influencing travel behaviour. Factor analysis is used as a data reduction tool to synthetise different statements that were included in the survey to understand respondents' perceptions and attitudes towards COVID-19.

A Poisson regression model is estimated for the number of one-way weekly trips for each purpose type, location (metropolitan or regional area) and working status in late 2020. In total, 16 models were estimated for the workers in both metropolitan and regional areas and 12 for non-workers (which do not consider commuting or work-related trips). The dependent variables, the number of one-way weekly trips for each purpose, are non-negative discrete count values, with truncation at zero, which are defined as a discrete random variable, y_i, observed over one period of time. The Poisson regression probability is given by equation (1).

$$P(y_i = k \mid \mu_i) = \frac{\exp(-\mu_i) \cdot \mu_i^k}{k!} \qquad k = 0,1,... \tag{1}$$

The prediction rate, μ_i, is both the mean and variance of y_i and is defined as follows:

$$\mu_i = E(y_i = k \mid x_i) = \exp(\beta' x_i) \tag{2}$$

The prediction rate or expected frequency of the number of days WFH was calculated as a function of different explanatory variables, shown in equation (3).

$$\mu_i = \exp\left(\beta_0 + \sum_n \beta_n \cdot z_n \cdot d_a + \sum_m \beta_m \cdot x_m \cdot d_a + \sum_f \beta_f \cdot x_f + \varepsilon\right) \tag{3}$$

where β_0 represents the constant; z_n represents respondents socio-demographics (e.g., age, gender, income); x_m other respondents' characteristics such as distance from home to work, mode used, etc.; d_a dummy variables associated to each area; x_f represents the factor attributes to underlying attitudes towards COVID-19; and the β represent the parameter estimate associated to each of the variables.

The marginal effects in this nonlinear model specification are presented in equation (4).

$$\text{Marginal Effects} \Rightarrow \frac{\partial E(y_i \mid x_i)}{\partial x_i} = \beta_i \cdot \mu_i = \beta_i \cdot E(y_i \mid x_i) \tag{4}$$

The direct point elasticities are presented in equation (5).

$$\text{Elasticity} \Rightarrow \frac{\partial E(y_i \mid x_i)}{\partial x_i} \cdot \frac{x_i}{E(y_i \mid x_i)} = \beta_i \cdot x_i \tag{5}$$

The direct point elasticity formula indicates that a one percentage change in the i^{th} regressor, *ceteris paribus*, leads to a one percentage change in the rate or expected frequency of $\beta \cdot x_i$. In contrast, where a variable is a dummy variable (1,0), a one percentage change is inappropriate, and a direct arc elasticity form is used as given in equation (6).

$$\text{Arc Elasticity} \Rightarrow \frac{E(y_i \mid x_1) - E(y_i \mid x_2)}{x_1 - x_2} \cdot \frac{(x_1 + x_2)/2}{\left(E(y_i \mid x_1) + E(y_i \mid x_2)\right)/2} = \frac{E(y_i \mid 1) - E(y_i \mid 0)}{E(y_i \mid 1) + E(y_i \mid 0)} \quad (6)$$

The arc elasticity interpretation is equivalent to the direct elasticity presented in equation (5) but it has to be multiplied by 100 to represent a 100% change (from 1 to 0, or 0 to 1).

In the survey, respondents were asked to answer several attitudinal questions that referred to their concern about using public transport (PT), their attitude towards working from home (WFH), their concern about health, among others. The first step was to use the Kaiser-Meyer-Olkim (KMO) test to measure sampling adequacy (Kaiser & Rice, 1974) and the Bartlett's Test of Sphericity (Bartlett, 1951) – both of which suggested that a factor analysis may be useful with our data. Parallel analysis is used to identify the number of factors to be used, which is used to compare the size of the eigenvalues with those identified by a set of data of the same size generated randomly (Horn, 1965). The attitudinal questions that refer to work from home are only valid for those respondents that are currently employed, so a separate analysis was performed for these questions for workers only. The parallel analysis results suggested that 5 factors should be considered for all the sample, and 1 for workers in relation to the WFH attitudinal questions. Having defined how many factors should be retained, the method of extraction used was maximum log-likelihood with oblique rotation. This method was used over restricting the factor to be orthogonal because attitudes are rarely statistically independent. The six factors extracted were the following:

1. WFH lovers: positive attitude towards WFH, which is only appropriate for workers.
2. Authorities and community's response supporters: respondents that believe the authorities and community response towards the pandemic has been appropriate.
3. Social meeting lovers: respondents that feel comfortable having social meetings with friends, visiting restaurants and pubs, gyms and exercise groups, among others.
4. All meeting lovers: respondents that feel comfortable having any type of meeting, including music events, watching live entertainment, among others,
5. Concerned about health: respondents that are concerned about theirs and others health and general COVID-19 implications.
6. Concerned about public transport: people that are concerned about hygiene and the number of people in public transport due to COVID-19.

5 MODEL RESULTS

5.1 Models for Workers in Metropolitan Areas

The models results for the workers in metropolitan areas are presented in Table 2. It is important to mention that the commuting model was only estimated for those respondents that worked outside the home for at least one day (e.g., commuted) as their behaviour is significantly different from those that never commuted, so it is not appropriate to model them together. The parameter estimates

suggest that different sociodemographic characteristics explain commuting and non-commuting travel behaviour for metropolitan workers. For example, income has a positive influence on commuting and social recreation trips for all regions, and a positive influence on shopping trips only in QLD (it was not statistically significant in NSW). The number of children in a household has a negative influence on work-related and social recreation trips, but a positive influence on education and shopping trips for all regions – and a positive influence on commuting trips in QLD. Results show that the proportion of days WFH has a negative influence on commuting and work-related trips, as expected, but a positive influence on the number of education and shopping trips, and in NSW it also has a positive influence on the number of personal business and social/recreation trips. As people work more days from home, they also tend to increase their non-commuting weekly trips. The interaction term between the factor WFH lover and proportion of days WFH has a statistically significant and positive influence on commuting trips for both states (but lower in absolute value than the parameter proportion of days WFH). This suggests that, even though people that WFH more often tend to commute less, people that enjoy working from home tend to do more commuting trips than those who do not enjoy it. This is an interesting finding that suggests that liking WFH does not strictly mean there is a dislike to commute. In NSW, this interaction term had a significant and negative influence on social/recreation trips, which shows that people that WFH more often tend to do more social/recreation trips, but those that enjoy WFH tend also on average to do less social/recreation trips than those who do not enjoy it.

The factor related to the authorities and community response only had a statistically significant and positive influence on shopping trips, indicating that individuals that are supportive towards the response of authorities in particular tend to do more shopping trips. This may be linked to bio-security issues and how they have been handled by State governments where the confidence in getting out and about for essential services is positive. The result for the social meetings factor suggests that people that feel comfortable going to social meetings tend to do more shopping, personal business and social/recreation trips, but less education trips. This may be in part due to ease with education can be undertaken online in contrast to the other trip purposes where face to face interaction is more important. Respondents that feel comfortable going to all meetings (including massive gatherings), tend to do more work-related, shopping and social/recreation trips but less commuting trips, possibly because it is easier to WFH in contrast undertaking the other purposes in the home. Individuals that are concerned about health also tend to do more personal business, however, those that use car to go to work (the week prior to the survey) tend to do less personal business trips. The interaction between commuting by car and being concerned about health had a positive influence on commuting trips and social/recreation trips, suggesting that those that are concerned about health and used the car to commute tend to do more of these trips relative to those that do not use the car to commute or are less concerned about health. Respondents concerned about the use of public transport tend to do less social/recreation trips in both states, but more personal business trips in NSW only.

Clearly, what we have is evidence of a significant amount of preference heterogeneity in trip making behaviour linked to socioeconomic characteristics and attitudinal positions. The ability to link particular trip making across all trip purposes as commuting activity changes due to the growing incidence of WFH, enables planners to gain a richer picture of the quantum of trips on the roads and on public transport.

5.2 Models for Workers in Regional Areas

The results for regional area worker models are presented in Table 3. Income has a positive influence on the number of commuting and work-related trips for both states, and a negative influence on personal business trips in QLD. The number of children has a negative influence on the amount of commuting and work-related trips and a positive influence on the number of education trips. The proportion of days WFH has a negative influence on the number of commuting and work-related trips, and a positive influence on the number of social/recreation trips. The interaction term between WFH lovers and the proportion of days WFH has a negative influence on social/recreation trips. That is, respondents that WFH more often tend to do more social/recreation trips, but if they are WFH lovers they tend to do less trips than those that do not enjoy WFH as much.

The factor results suggest that people that have greater support for the government and wider community's response to COVID-19 tend to do undertake fewer work-related trips in both states; and in QLD they tend to do more commuting trips while in NSW it is fewer commuting trips. People that feel comfortable going to social meetings tend to do more work-related, shopping, personal business, and social/recreation trips; while people that feel comfortable going to all meetings (including massive gatherings) tend to do more education and shopping trips in both states, and less commuting trips in NSW. People that are concerned about health tend to do fewer commuting trips, but those that used car to go to work, tend to do more commuting trips than those that use other modes. Oppositely, respondents concerned about health tend to do more social/recreation trips, but those that use car to go to work tend to do less social/recreation trips than those that use other modes. Respondents that are more concerned about their health tend to do more work-related trips in QLD area, and those that also use car to go to work tend to do more education trips. Again, like metropolitan evidence, there exists a significant amount of heterogeneity in the influencing variables across the trip purposes, with this evidence being important in identifying patterns of trip making behaviour for particular origin-destination pairs during the COVID-19 period as WFH levels change in part linked to reduced levels of commuting. However, unlike metropolitan areas, commuting levels have not declined much at all, with WFH not having a statistically significant influence for three of the six trip purposes.

5.3 Models for Non-workers Metropolitan Areas

The model results for non-workers in metropolitan areas are summarised in Table 4. The results show that, for example, income has a negative effect on the number of education trips, and a positive influence for social/recreation trips. Age has a negative effect on the number of education, shopping and personal business trips. The factors' results suggest that people who support authorities and community's response to COVID-19 tend to undertake more personal business trips which might suggest that they trust the effectiveness of the measures being taken by authorities and therefore do personal business trips which might be considered essential. People that feel comfortable going to social meetings tend to undertake more education, shopping and social/recreation trips, while people that feel comfortable going to larger gatherings (all meetings) tend to do more education and shopping trips, but less personal business trips. Individuals concerned about health and bio-security tend to have more personal business trips; and in QLD they only tend to do less social/recreation trips. People that are concerned about the bio-security associated with public transport tend to do less shopping, personal business and social/recreation trips.

Table 2: Model estimates for respondents currently employed (workers) located in metropolitan areas – mean (t value)

Metropolitan workers	Commute	Work-related	Education	Shopping	Personal business	Social/ recreation
Constant	2.382 (32.39)	0.305 (2.82)	-0.616 (2.85)	1.411 (25.22)	-0.067 (0.39)	0.899 (8.69)
Age (years)	-0.009 (5.92)		-0.022 (4.91)		-0.012 (3.61)	
Gender female (0,1)		-0.682 (7.70)	0.564 (6.31)	-0.090 (2.15)		-0.092 (1.62)
Personal income ('000AUD$)	0.001 (1.73)					0.002 (3.78)
Personal income in QLD State ('000AUD$)				0.001 (1.90)		
Number of children in household		-0.146 (3.06)	0.366 (9.57)	0.089 (4.62)		-0.080 (3.24)
Number of children in household in QLD State	0.038 (1.60)					
At least one child in primary school (0,1)	-0.083 (1.67)	0.368 (2.84)	1.153 (10.95)	-0.120 (1.94)		
Number of cars per adult in household	0.087 (3.10)	0.425 (8.61)	0.335 (6.60)		0.197 (3.76)	0.095 (2.32)
Distance from home to office (kms)	-0.001 (1.79)	0.003 (3.89)	-0.007 (2.77)	-0.003 (3.46)		
Proportion of days WFH	-1.482 (4.45)	-0.657 (5.89)	0.578 (6.13)	0.110 (2.24)		
Proportion of days WFH in NSW State					0.849 (2.75)	0.221 (2.72)
Occupation clerical and administration (0,1)	0.083 (1.69)	-0.358 (2.80)				
Used car to go to work last week (0,1)	-0.329 (7.46)	-0.304 (3.14)	-0.335 (3.41)	-0.131 (2.74)	0.300 (2.68)	-0.137 (2.17)
Work located in CBD area (0,1)			-0.434 (3.48)	0.143 (2.75)		
Central Coast (0,1)					-0.608 (3.02)	
Brisbane (0,1)	-0.126 (2.49)	-0.656 (4.44)			-0.305 (2.52)	-0.298 (3.46)
Located in the state of NSW (0,1)			-0.453 (5.46)			-0.195 (2.55)
Factor analysis: authorities and community response				0.046 (2.11)		
Factor analysis: social meetings			-0.071 (2.12)	0.124 (5.91)	0.192 (5.13)	0.338 (10.82)
Factor analysis: all meetings	-0.046 (2.98)	0.114 (3.43)		0.091 (4.81)		0.158 (5.88)
Factor analysis: concerned about health					0.378 (3.50)	
Factor analysis: public transport concerned						-0.144 (5.13)
Interaction between factor analysis: public transport concerned and NSW State					0.161 (2.79)	
Interaction between factor WFH lover and proportion of days WFH	0.435 (1.61)					
Interaction between factor WFH lover and proportion of days WFH in NSW State					-0.603 (2.40)	
Interaction between factor concerned about health and use of car to go to work last week	0.064 (2.00)				-0.323 (2.77)	0.099 (2.77)
Restricted log-likelihood	-1,677.13	-1,252.83	-1,430.93	-938.71	-1,051.40	-1,669.38
Log-likelihood at convergence	-1,561.53	-1,130.72	-991.88	-1,784.12	-999.30	-1,559.46
AIC/n	6.72	3.65	3.20	5.73	3.23	5.02
Sample size	469	627	627	627	627	627

*Note: The commuting model only considers those individuals that commute sometimes. Respondents that never commuted (i.e., worked from home every day) had a different behaviour, so could not be modelled together.

Table 3: Model estimates for respondents currently employed (workers) located in the regional area – mean (t value)

Regional workers	Commute	Work-related	Education	Shopping	Personal business	Social/ recreation
Constant	1.939 (20.58)	-0.108 (0.63)	-0.423 (1.98)	1.468 (14.10)	1.355 (6.22)	1.250 (9.60)
Age (years)	-0.008 (4.26)		-0.016 (3.40)		-0.014 (3.18)	-0.005 (1.81)
Gender female (0,1)		-0.445 (3.72)	0.744 (6.46)	0.137 (2.14)		
Personal income ('000AUD$)	0.003 (5.90)	0.006 (5.67)				
Personal income in QLD State ('000AUD$)					-0.005 (3.29)	
Number of children in household	-0.053 (3.18)	-0.087 (1.76)	0.395 (10.68)			
At least one child in primary school (0,1)			0.716 (5.71)			-0.248 (2.42)
Number of cars per adult in household		0.163 (2.03)				-0.125 (2.25)
Distance from home to office (kms)		-0.008 (2.18)	-0.006 (2.78)			-0.004 (2.17)
Proportion of days WFH	-0.839 (4.70)	-1.026 (3.94)				1.918 (4.85)
Occupation clerical and administration (0,1)		-0.541 (3.41)				0.217 (2.47)
Occupation manager (0,1)						0.373 (3.41)
Occupation sales (0,1)						
Industry category retail (0,1)		-0.904 (3.96)				
Used car to go to work last week (0,1)					-0.685 (4.30)	
Used car to go to work last week in QLD State (0,1)	0.167 (2.98)					
Prior to COVID-19 used car to go to work (0,1)				-0.252 (2.44)		
Factor analysis: authorities and community response		-0.205 (3.51)				
Factor analysis: authorities and community response in QLD State	0.104 (3.30)					
Factor analysis: authorities and community response in NSW State	-0.103 (2.54)					
Factor analysis: social meetings		0.307 (6.30)		0.090 (3.25)	0.132 (3.03)	0.128 (4.27)
Factor analysis: all meetings			0.073 (2.21)	0.044 (1.73)		
Factor analysis: all meetings in NSW State	-0.088 (2.83)					
Factor analysis: concerned about health	-0.322 (3.51)					0.310 (2.78)
Factor analysis: concerned about health in QLD State		0.126 (2.10)				
Interaction between factor WFH lover and proportion of days WFH						-1.893 (5.70)
Interaction between factor concerned about health and use of car to go to work last week	0.370 (4.00)		0.148 (3.12)			-0.236 (2.05)
Restricted log-likelihood	-897.41	-672.33	-861.89	-818.60	-577.74	-860.37
Log-likelihood at convergence	-828.06	-573.31	-617.22	-808.30	-551.89	-803.07
AIC/n	5.87	3.76	4.02	5.23	3.58	5.24
Sample size	286*	311	311	311	311	311

*Note: The commuting model only considers those individuals that commute sometimes. Respondents that never commuted (i.e., worked from home every day) had a different behaviour, so could not be modelled together.

5.4 Models for Non-workers Regional Areas

The model results for non-workers in regional areas are presented in Table 5. The results show that, income has a positive effect on social/recreation trips, and only in QLD a positive effect on education and personal business trips. Age has a negative effect on education trips and a positive influence on the number of personal business trips. The factors' results show that people that support authorities and community's response to COVID-19 tend to do more social/recreation trips, and only in QLD they have fewer education trips.

People that feel comfortable going to social meetings tend to undertake a greater number of education and social/recreation trips, while individuals that feel comfortable going to larger gatherings (all meetings) tend to have a higher number of education and social/recreation trips but undertake less shopping and personal business trips. People that are concerned about health in NSW tend to do fewer education trips.

Table 4: Model estimates for respondents not currently employed (non-workers) located in metropolitan areas – mean (t value)

Metropolitan non-workers	**Education**	**Shopping**	**Personal business**	**Social/ recreation**
Constant	2.988 (10.13)	2.013 (13.40)	0.836 (2.94)	0.663 (7.22)
Age (years)	-0.057 (11.22)	-0.009 (4.34)	-0.026 (6.46)	
Gender female (0,1)	-1.016 (6.03)	-0.181 (2.68)	-0.355 (2.66)	
Personal income ('000AUD$)	-0.006 (2.48)			0.004 (4.25)
Number of children in household	0.541 (14.78)	0.149 (6.43)	-0.227 (3.26)	-0.102 (2.58)
Number of cars per adult in household			0.629 (6.24)	0.324 (5.35)
Brisbane (0,1)	-0.664 (2.51)			
Located in the state of NSW (0,1)		-0.164 (2.53)	0.393 (2.77)	-0.213 (2.67)
Factor analysis: authorities and community response			0.254 (3.56)	
Factor analysis: social meetings	0.482 (6.38)	0.226 (6.54)		0.257 (7.60)
Factor analysis: all meetings	0.219 (3.11)	0.114 (3.47)	-0.119 (1.99)	
Factor analysis: concerned about health			0.321 (3.68)	
Factor analysis: concerned about health in QLD State				-0.107 (1.76)
Factor analysis: public transport concerned		-0.126 (4.22)	-0.096 (1.62)	-0.164 (4.90)
Restricted log-likelihood	-621.49	-800.52	-555.45	-854.00
Log-likelihood at convergence	-367.74	-738.48	-509.15	-783.81
AIC/n	2.79	5.55	3.86	5.89
Sample size	269	269	269	269

Table 5: Model estimates for respondents not currently employed (non-workers) located in the regional area – mean (t value)

Regional non-workers	**Education**	**Shopping**	**Personal business**	**Social/ recreation**
Constant	-1.100 (1.65)	1.428 (14.60)	-2.516 (4.28)	0.752 (4.64)
Age (years)	-0.027 (2.95)		0.017 (2.38)	
Gender female (0,1)	0.635 (1.99)	0.274 (2.99)		0.273 (2.04)
Personal income ('000AUD$)				0.008 (4.22)
Personal income in QLD State ('000AUD$)	0.016 (30.00)		0.024 (3.03)	
Number of children in household	0.572 (8.33)			-0.123 (2.36)
Number of cars per adult in household				0.206 (2.81)
Located in the state of NSW (0,1)		-0.372 (4.04)	0.854 (1.77)	-0.729 (5.75)
Factor analysis: authorities and community response				0.095 (1.70)
Factor analysis: authorities and community response in QLD State	-0.822 (6.05)			
Factor analysis: social meetings	0.252 (2.34)			0.212 (3.22)
Factor analysis: all meetings	0.214 (1.99)	-0.083 (2.46)	-0.306 (3.70)	0.173 (2.95)
Factor analysis: concerned about health in NSW State	-0.428 (3.40)			
Restricted log-likelihood	-277.95	-410.42	-192.23	-408.70
Log-likelihood at convergence	-137.40	-396.19	-173.12	-375.78
AIC/n	2.08	5.68	2.53	5.46
Sample size	141	141	141	141

5.5 Elasticities

We have calculated the point and arc direct elasticities as an informative way of identifying the sensitivity of trip frequency to levels of each explanatory variable. They represent the relationship between the expected frequency of the number of weekly one-way trips and the statistically significant influences. All elasticities are relatively inelastic. Table 6 presents the elasticities for workers in metropolitan areas and Table 7 in regional areas; while Table 8 presents the elasticities for non-workers in metropolitan areas and Table 9 in regional areas.

The elasticity of age in the commuting trips model is of -0.350 in metropolitan areas and -0.310 in regional areas, which indicates, *ceteris paribus*, that a person 10% older is (e.g., 24 years old relative to 20 years old) undertakes 3.5% fewer one-way weekly commuting trips in metropolitan areas and 3.1% fewer in regional areas. Given that elasticities are unitless and hence directly comparable, we can see that the elasticities associated with age create the greatest behavioural change across three trip purposes with a number of relatively high elasticities for some variables in some trip purpose models. Age has a significantly higher influence on non-workers education and personal trips. A person who is 10% older is likely to do 8.7% less education trips if he/she is a metropolitan area worker; 6% if he/she is regional area worker; 33.4% if he/she is a non-worker in a metropolitan area; and 15.6% if he/she is a non-worker in regional areas compared to someone 10% younger. This provides evidence that older people not currently employed are significantly less likely to undertake education trips than those currently employed, particularly if they live in metropolitan areas.

Table 6: Elasticities for the models of workers located in metropolitan areas

Metropolitan workers	Commute	Work-related	Education	Shopping	Personal business	Social/ recreation
Age (years)	-0.350		-0.870		-0.496	
Gender female (0,1)		-0.328	0.275	-0.045		-0.046
Personal income ('000AUD$)	0.052			0.022		0.146
Number of children in household	0.016	-0.162	0.405	0.099		-0.089
At least one child in primary school (0,1)	-0.041	0.182	0.520	-0.060		
Number of cars per adult in household	0.103	0.485	0.382		0.224	0.108
Distance from home to office (kms)	-0.026	0.053	-0.131	-0.067		
Proportion of days WFH	-0.132	-0.231	0.204	0.039	0.039	0.053
Occupation clerical and administration (0,1)	0.042	-0.177				
Used car to go to work last week (0,1)	-0.165	-0.151	-0.166	-0.065	0.158	-0.073
Work located in CBD area (0,1)		0.123	-0.213	0.071		
Central Coast (0,1)					-0.295	
Brisbane (0,1)	-0.063	-0.317			-0.151	-0.148
Located in the state of NSW (0,1)			-0.223			-0.097

Similarly, a person who is 10% older than someone else is likely to undertake 5% less personal business trips if he/she is a metropolitan area worker; 5.2% if he/she is regional area worker; 15.4% if he/she is a non-worker in a metropolitan area; and 9.7% more personal business trips if he/she is a non-worker in regional areas. This suggests that older respondents not currently employed tend to undertake more personal business trips in regional areas, relative to younger respondents. This relationship is opposite in regional and metropolitan area workers and metropolitan area non-workers, where older respondents tend to do less personal business trips than younger respondents.

Table 7: Elasticities for the models of workers located in regional areas

Regional workers	Commute	Work-related	Education	Shopping	Personal business	Social/ recreation
Age (years)	-0.310		-0.599		-0.524	-0.193
Gender female (0,1)		-0.219	0.356	0.068		
Personal income ('000AUD$)	0.217	0.412			-0.212	
Number of children in household	-0.063	-0.103	0.468			
At least one child in primary school (0,1)			0.343			-0.124
Number of cars per adult in household		0.232				-0.178
Distance from home to office (kms)		-0.140	-0.119			-0.073
Proportion of days WFH	-0.052	-0.141				-0.052
Occupation clerical and administration (0,1)		-0.264				0.108
Occupation manager (0,1)						0.185
Industry category retail (0,1)		-0.424				
Used car to go to work last week (0,1)	0.080		0.009		-0.330	-0.015
Prior to COVID-19 used car to go to work (0,1)				-0.125		

Table 8: Elasticities for the models of non-workers located in metropolitan areas

Metropolitan non-workers	Education	Shopping	Personal business	Social/ recreation
Age (years)	-3.336	-0.499	-1.536	
Gender female (0,1)	-0.469	-0.090	-0.176	
Personal income ('000AUD$)	-0.212			0.138
Number of children in household	0.405	0.111	-0.170	-0.077
Number of cars per adult in household			0.591	0.305
Brisbane (0,1)	-0.320			
Located in the state of NSW (0,1)		-0.082	0.194	-0.106

Table 9: Elasticities for the models of non-workers located in regional areas

Regional non-workers	Education	Shopping	Personal business	Social/ recreation
Age (years)	-1.558		0.968	
Gender female (0,1)	0.307	0.136		0.136
Personal income ('000AUD$)	0.117		0.179	0.245
Number of children in household	0.515			-0.111
Number of cars per adult in household				0.231
Located in the state of NSW (0,1)		-0.184	0.403	-0.349

6 SIMULATIONS

Different scenarios were simulated that represent the behavioural sensitivity of the number of one-way weekly trips by purpose due to variations in the proportion of days WFH, distance from home to work and age. These explanatory variables did not have a statistically significant impact on all trips purposes' models, so only the statistically significant relationships will be analysed below. Figure 2 presents the simulation results for changes in the proportion of days WFH on the weekly one-way trips made by workers in metropolitan and regional areas. In both locations, the number of commuting trips decrease as the proportion of days WFH increases, as expected, and it decreases faster in metropolitan areas than regional areas. Work-related trips also decrease but at a slower rate when the proportion of days WFH increase. In metropolitan areas, the number of education and personal business weekly trips increase very similarly as the proportion of days WFH increases, with a slight increase in the number of shopping trips and social/recreation trips. In regional areas, there is a significant increase in the number of social/recreation trips as the proportion of days WFH increase. What these findings suggest is that there is an identified increase in all non-commuting trip activity when WFH increases and

its associated reduction in commuting in metropolitan areas, but this is not the case in regional contexts where only social/recreation trips are impacted by the WFH increase.

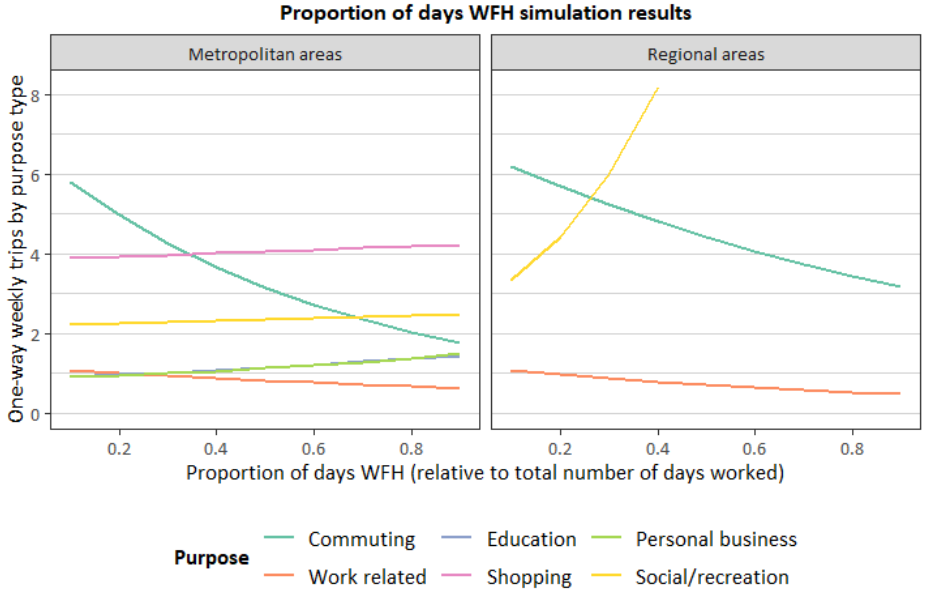

Figure 2: Proportion of days WFH simulation results

The distance from home to work simulation results, presented in Figure 3, suggest that people that work further from where they live in metropolitan areas, tend to do less commuting, shopping and education trips, but more work-related trips. It is important to note that the average number of commuting and shopping weekly trips is significantly higher than the education and work-related trips. In regional areas, people that work further from where they live tend to do less social/recreation, education and work-related trips. In regional areas, the average for social/recreation trips is higher than for the other two.

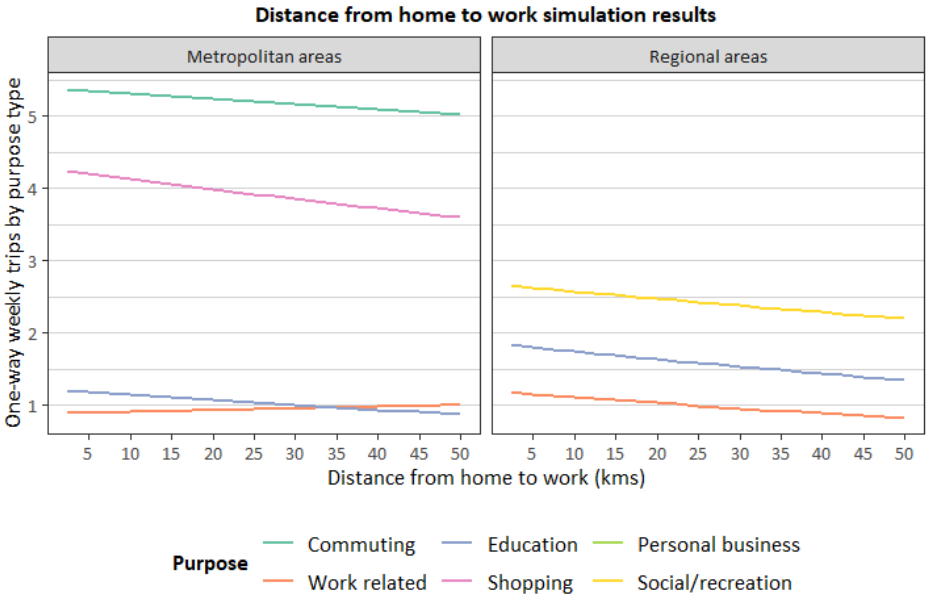

Figure 3: Distance from home to work simulation results

These results show the impact of a respondents' quantum of commuting trips on their non-commuting travel behaviour, suggesting that metropolitan area workers that have a longer

commuting trips usually do less of these trips, but also less shopping and education trips, and slightly more work-related trips. Workers in regional areas that have longer commuting trips tend to undertake less social/recreation, education and work-related trips.

7 CONCLUSIONS

This study's focus is to understand the impact of COVID-19 on commuting and non-commuting travel behaviour. The impact of COVID-19 is measured through the proportion of days WFH, which has increased significantly, especially in metropolitan areas, as a result of this health crisis, and through respondents' perceptions and attitudes towards COVID-19. The data in this study includes respondents from metropolitan and regional areas in two states in Australia, QLD and NSW, and includes workers and non-workers. A separate model is estimated for different trip purposes: commuting, work-related, education/childcare, shopping, personal business and social/recreation.

To include the underlying attitudes towards COVID-19, factor analysis was used, and six factors were extracted that represent WFH loving attitude, support towards authorities and wider community response, social meeting lovers, all meeting lovers (including massive gatherings), health concerned, and public transport concerned. These factors were included as explanatory variables in Poisson regression models, along with respondents' socioeconomic characteristics, other characteristics related to their work (e.g., distance from home to work) and location variables. The results suggest that attitudes towards COVID-19 have a significant influence on commuting and non-commuting travel activity. In metropolitan areas, people that WFH more often are less likely to undertake commuting trips, but if they love WFH to some extent then they are more likely to have commuting trips than individuals who do not love WFH. Workers that are concerned about the use of public transport due to COVID-19 are less likely to do work-related and social/recreation trips in metropolitan areas, and non-workers who are concerned are less likely to do shopping, personal business or social/recreation trips in metropolitan areas. In arriving at these findings, we have to recognise the real possibility that additional constraints that are not under the control of an individual may be at play such as less work for work-related travel and fewer people asking someone to visit them.

The results show that the proportion of days WFH has a significant impact on travel behaviour. As expected, it produces a reduction in the number of commuting and work-related trips in metropolitan and regional areas. Moreover, it generates an increase in shopping and education trips in metropolitan areas, and an increase in social/recreation trips in regional areas.

The findings in this study can be used as a guideline as to the impact of COVID-19 on weekly travel behaviour for commuting and non-commuting trips and to suggest changes to be made to strategic transport models where trip frequency is relevant. The impact of COVID-19 is measured both in terms of the proportion of days worked from home instead of the office, but also in terms of the attitudes and perceptions of COVID-19 in daily life. These measures affect workers and non-workers and people in metropolitan and regional areas. The long-term impacts of COVID-19 are yet to be seen, but it is expected that working from home will prevail where possible, as it has proven to have advantages in terms of time-use, productivity and life balance. Health concerns might also have a long-term effect, even after we have overcome this pandemic or learnt to live with it in a fully vaccinated setting. This study suggests that WFH, health concerns and general attitudes towards COVID-19 play an important role in all-purpose mobility trips and not just commuting activity.

ACKNOWLEDGEMENTS
This paper is a contribution to the ITLS research program on working from home. Post-Wave 2, the project has received funding from the iMOVE Cooperative Research Centre with industry partners, Transport and Main Roads Queensland, Transport for NSW and the Western Australian Department of Transport.

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