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What does the Quantum of Working from Home do to the Value of Commuting Time used in Transport Appraisal?

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TITLE: **What does the Quantum of Working from Home do to the Value of Commuting Time used in Transport Appraisal?**

ABSTRACT: The need to recognise and account for the influence of working from home on commuting activity has never been so real as a result of the COVID-19 pandemic. Given are cognition that WFH activity during the pandemic has reduced the amount of commuting activity compared to pre-COVID-19, the inevitable question is raised as to what this might mean for some of the crucial inputs in the appraisal of transport initiatives. One critical value used in benefit-cost analysis is the value of time which converts time into monetary units in the calculation of user benefits. We are interested in whether reduced commuting activity is associated with higher or lower willing to pay to save time. We investigate this possibility with data from the Greater Sydney Metropolitan Area in late 2020 when working from home was at a high level. The findings of a higher average commuter VoT have major implications for the VoT used in transport appraisal given that time savings are the largest user benefit. We suggest a percentage adjustment required to align with the 'new normal' as currently known.

KEY WORDS: ***COVID-19, working from home, Australian experience, commuter mode choice, value of time (VoT) distribution, mixed logit, change in VoT during COVID-19***

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1. Introduction

As commuters spend more time working from home (WFH), whether by choice or by directive as a consequence of COVID-19, the amount of time and money spent commuting over a week has changed, often quite substantially[1]. Although WFH is not available to all occupations and industries, it has changed to a significant degree since the beginning of the COVID-19 pandemic (in March 2020), and questions are being asked as to whether we will return to pre-COVID-19 levels of commuting activity as we move out of the pandemic (or indeed live with COVID-19 in a vaccinated world), whenever that is. With an increasing number of new strains (notably the UK, South African and Indian mutations), lockdown has occurred in many countries at the beginning of 2021 as a second or third spike or a continuation of the 2020 levels of transmission. Even though the promise of a vaccine has begun to be realised, the rollout will not be instant in many countries and the overall efficacy is still unknown.

Over the last 10 months to the end of 2020, we observed massive reductions in commuting activity which have, in some countries, slowly increased but to a level that is well below the pre-COVID-19 level. For example, in the Greater Sydney Metropolitan Area (GSMA) and South East Queensland (SEQ) in September 2020, we found that close to 50% of the pre-COVID-19 commuting time outlays were 'saved'[2]. On average, each commuter saved $2,949 per annum in the SEQ and $3,546 in the GSMA[3], of which $779 and $906 respectively is out of pocket costs. These are sizeable reductions, and while we might expect this quantum in savings to be less in time as we find more workers returning to their traditional office[4], WFH is likely to continue at significant levels, supported by employers and the preferences of employees (Beck and Hensher 2020, 2020a).

With a reduced outlay of time and money for commuting, an obvious question to ask is what this might mean for the values of travel time used in generalised cost calculations and transport appraisal? With the real possibility of revised time and cost budget constraints defining potentially greater unspent commuting time and money compared with pre-COVID-19 associated with commuting, individuals on average are expected to have additional income and time available for other activities (including non-commuting travel), but also are likely to have a revised view on the sensitivity they have to outlays of travel time and cost for commuting, including which mode to use (see Figure 1 for the GSMA). One possibility is that the budgeted levels associated with tolerance to outlays of commuting time and cost may be revised as the amount of weekly commuting changes. At one extreme we have workers who now WFH all the time and they may now have a preference function (because of the available choice) that is associated with a very high willingness to pay to save travel time, *ceteris paribus*, on the reduced occasion of commuting simply because the trip is no longer so essential but often discretionary[5]. This is an example of a very low level budget threshold of acceptance. In contrast, someone who works from home very little (including not at all), is more likely to get used to a certain higher (in relative terms) threshold level and hence are less sensitive to levels of travel time and/or cost, and thus place a lower value on saving a unit of time. The implication for an average value of time (VoT), weighted or otherwise, by the incidence of the number of weekly days WFH, is that it is likely to change as the incidence of WFH is greater, although whether it will be higher

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[1] The focus of this paper is on the commuting trip between an individual's home and a regular work location. We do not include people who travel as part of their work.

[2] Hensher et al. (2021) present the equivalent evidence for late May 2020. All dollars are in $AUD.

[3] Based on the recommended (pre-COVID-19) VoT of each State government

[4] In Australia there is a strong push for only 25% of public servants and 50% of private sector business employees to be in the office at any one time for at least the next year. Almost daily there are media reports of surveys suggesting significant resistance to returning to the traditional office.

[5] There is growing anecdotal evidence that the desire to get out of home and go to work to obtain some much needed social interaction is resulting generally in disappointment as few are in the office at any one time.

or lower on average is unknown; but that regardless of the directional impact, the distribution of the value of time is likely to be non-linear given the skewed distribution of days WFH (Figure 2 for the GSMA), and to vary for example, by income and distance to the regular workplace.

In addition to possible changes in commuting travel budgets, there are a number of additional features of the COVID-19 period that we must consider that have the potential to influence the commuting trip travel time and cost trade-off. Modal switching for the commute (Figure 1) can occur for at least two reasons - a bio security concern in using public transport and ride share, and the desire to use a car because of greater affordability (parking and tolls in particular) due to reduced weekly commuting.

We suggest that a change in VoT could be, in part, due to an added "biosecurity" premium, with the resulting VoT related to minimising travel time on a currently perceived "risky" alternative (Nelson 2021). To account for this biosecurity concern, we have used a 5-point rating variable represented as a dummy variable for high level of concern (defined by the moderate and extreme levels of concern) which has been shown also in Beck et al. (2021) to be highly correlated with crowding where the latter is also related to a health concern. There may also be different mixes of commuters since some occupations have a greater or lesser propensity to be able to WFH and we add these in. Beck and Hensher (2020) show that the main groups that are more likely to WFH are professionals and managers.

The concern over using PT as a proxy for health and crowding is included in the PT modes, and the occupation effects in all modes as interactions with travel time so that they might influence the VoT. The mode switching dummy variables are included in the alternative associated with mode a respondent switches to. We also considered changing residential location or main regular office, but there were so few such changes.

We recognise that we are estimating models at one point in the COVID-19 progression (i.e., late 2020) and that is why we are undertaking regular surveys to continue to see how VoT is moving and hopefully settling to a new level associated with the new or better normal. The VoT estimates presented in this paper are a very relevant positioning set after six months of COVID-19, in September 2020.

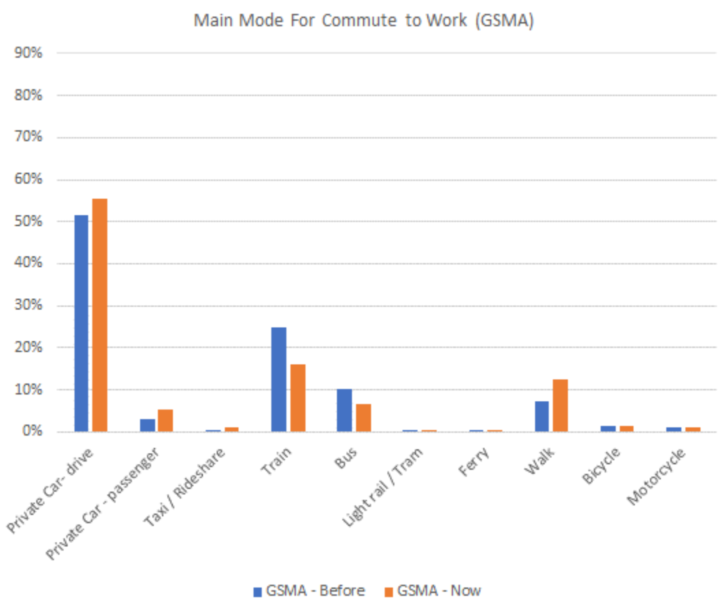

Figure 1: Commuter Mode Changes, pre-COVID-19 and September 2020

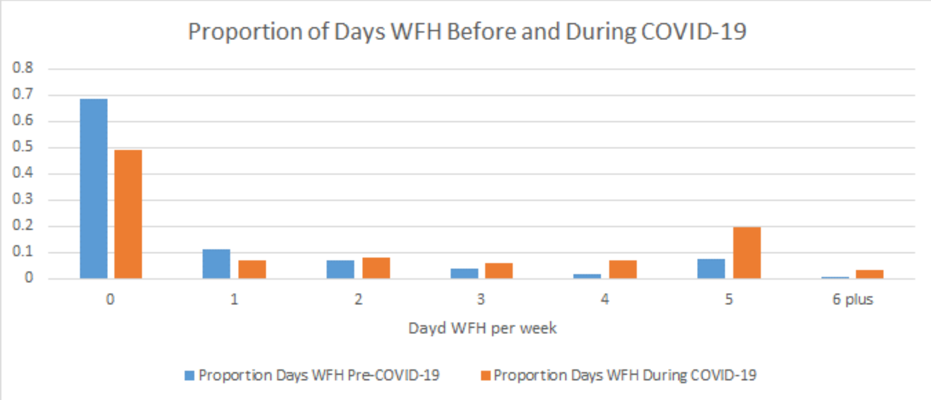

Figure 2: Distribution of Days WFH in 2019 and September 2020

The direction of causality of the joint increase in the number of days WFH and average commuter VoT is not clear. A lower estimate might be because individuals who tend to commute more due to the nature of their work (i.e., essential services), tend to have lower personal incomes and hence represent the population of commuters who generally have a lower mean estimate of VoT. Hensher at al. (2021) ran a simple model of the relationship between the number of days WFH and personal income and obtained a direct elasticity of 0.298 (standard error of 0.0059) for the SEQ and 0.282 (standard error of 0.0055) for the GSMA[6]. What this indicates is that there is a possible relationship between those who commute more and personal income, indicating that a 1 percent increase in income results, ceteris paribus, in a 0.298 (SEQ) or 0.282 (GSMA) percent increase in the number of days WFH. This relationship has to be weighed against a position that reduced commuting activity may mean that an individual is willing to pay more to save time simply because they commute less and the burden of commuting time and cost outlays is reduced. . We interact income with travel time in deriving empirical estimates of VoT that are influenced by income.

The objective of this paper is to empirically investigate this matter further and to see to what extent (if at all) the commuter VoT does increase or decrease with increasing days WFH in the GSMA area; and to comment on how the mean estimate compares to recommended (in government guidelines) pre-COVID-19 VoT values in the GSMA. We add an important caveat. By engaging in WFH, individuals have more time *and* income at their disposal to spend on non-commuting activities, so that the marginal utility of both associated with the commute decreases. The ratio between both (i.e. the VoT) may decrease, increase, or remain unchanged, a testable proposition. In our model we allow for the marginal utility of income and tested the amount of time committed to commuting pre-COVID-19 (defined as one-way trip travel time of the proportion of travel time outlaid per week during COVID-19 compared to before) as a good proxy for a time budget threshold which is now relaxed in order to reveal the role of time and budget constraints in this context[7].

The paper is organised as follows. In the next section we provide a brief literature review with a focus on the role of various attributes in travel choice and their influence on VoT. We do not review the

[6] We also have evidence that it tends to be those in white collar occupations (managers/professionals/clerical and admin), the first two occupational groups of whom are typically on higher incomes.

[7] A referee suggested that an activity-based model with two alternative schedules (WFH vs. travel to/work in the office) is an appealing way to capture the changes in the good-leisure framework caused by WFH. While we agree we would argue that the approach in this paper provides a way of at least recognising the role that WFH plays is releasing time and money from commuting to be used on other activities (undefined). On these other activities we provide some evidence on the allocation to additional paid and unpaid work as well as increased leisure as well as how the money released might be used.

literature on working from home (or teleworking) given that much of the material has been summarised and commented on in detail in Beck and Hensher (2020, 2020a) and Beck et al. (2020), which list many of the main contributions by different authors. We then provide a descriptive profile of the context within which we are modelling the role that WFH and other considerations, such as income, occupation and concern about using public transport, play in a commuter mode choice model for the GSMA. We then present the way in which we have represented the role of the incidence of working from home in a mixed logit commute mode choice model, followed by the model results for the GSMA and the important behavioural findings. The paper concludes with a summary and suggested ongoing research activity.

2. Brief Literature Review on context setting for key influences on the Value of Commuting Time

The value of travel time is one of the most important behavioural outputs from travel behaviour studies and continues to have a significant role to play in decisions made for transport infrastructure investments and service improvements. As a dominant user benefit, there has accumulated a significant body of literature on both theoretical and empirical approaches to valuing travel time (e.g., Hensher 2011, Jara Diaz 2000, 2007, Batley et al. 2019, Daly and Hess 2020). A key consideration in establishing a theoretically rigorous and behaviourally meaningful VoT is to recognise the role of time and money budget constraints that define the utility space within which individuals assess the role of specific attributes such as travel time and travel cost in making travel choices. Historically, the commuter mode choice model has been the main model used to obtain estimates of VoT, with distributions that account for preference heterogeneity either through random parameters and/or interactions of time and/or cost with contextual characteristics such as personal income, or simpler choice models that retain preference homogeneity and obtain a single mean estimate of VoT.

Although the typical daily commuter trip continues to be the basis of identifying the role of various modal attributes, empirically identified from revealed and stated preference data, it has always, implicitly at least, been assumed that the cycle of repeated commuting activity remains constant and typically at 5 days a week with some small amount of telecommuting (evidentially so small that it is ignored). Furthermore, it has been assumed that there is a well-defined time and money budget allocated to commuting that accommodates a fixed period of time such as a five-day week. Writing out a utility expression subject to these constraints results in the well-known VoT result which has its roots in classic papers such as DeSerpa (1971) with elaborations and refinements by Jara Diaz (2007) and others. The important result is that there exist technical constraints relating to time and goods that establish that the consumption of a given good requires a minimum assignment of time. The formal model resulted in identifying the value of time in a specific activity. Therefore, the value of saving time in a constrained activity is equal to the value of leisure (or work) minus its marginal utility value (presumably negative). For more information see Jara-Diaz (2000, 2007) and Appendix B.

Several studies have addressed the issue of how the VOT changes due to different factors. An important result from Rich and Vandet (2019) of relevance to a setting of major disruption, using the data collected from a Danish national travel survey from 2006 to 2016, is that the VOT changed over time, increasing approximately 10% over the 10-year period, with the global financial crisis (GFC) having a significant impact on the average VOT as well as the differing values for each income group.
There are many studies we can cite that have investigated how VoT varies according to the nature of activities undertaken during the travel experience. For example, Varghese & Jana (2018) in Mumbai show that there was a 26% reduction in VOT for those individuals who perform multi-tasking such as using social media, conversed on the smart phone and played digital games (also shown in Wardman, Chintakayala, & Heywood (2020). Kouwenhoven & de Jong (2018) using stated preference data in the Netherlands context, suggest that people who can spend their time usefully have a lower VOT and

having a computer available during the trip increases the probability of travel time being useful. In 2021 it is reasonable to assume that such multi-media capability has already impacted on the VoT regardless of the number of days commuting compared to WFH. Additionally, we might relate this to working from home (Figure 3) where the time not commuting is converted, on average, to greater perceived productivity associated with a new experience, namely WFH (although we have no data in productivity while commuting). Their results also suggest that travellers who said a shorter trip duration is useful or longer trip duration is very inconvenient, have a higher VOT. This might be equivalent to the reduced amount of commuting travel over a week in the growing presence of WFH. What these studies, as examples, indicate is that within the commuting activity, the disutility effects of travel in addition to the opportunity cost of time vary substantially and contribute to a distribution of VoT that results in higher or lower VoT depending on the positive or negative nature of additional activities for a given travel time and travel cost outlay. The overlay of WFH is also suggestive of a definite change in the VoT with fewer weekly commuting trips.

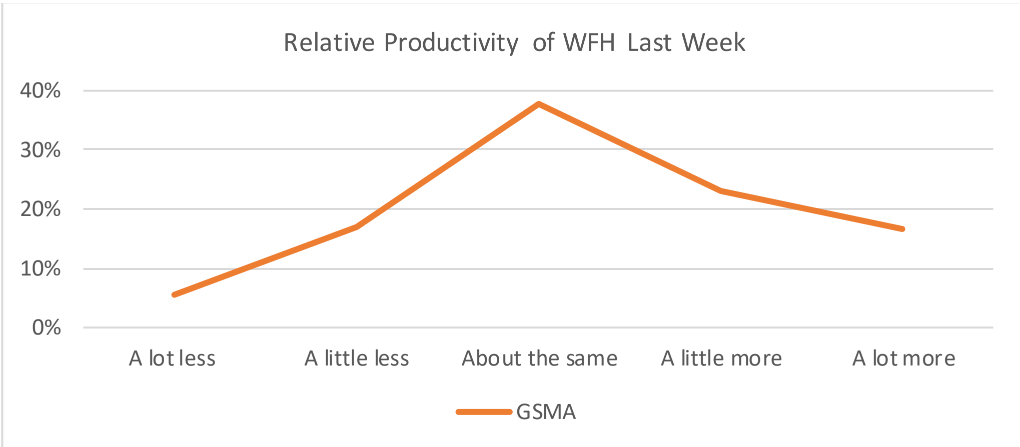

Figure 3: Perceived productivity associated with WFH, September 2020 (Beck et al. 2020)

With the exception of the reference to the GFC as a major external shock, the other effects represented as examples above, are all related to the travel experience and are not reflective necessarily of the role that other significant exogenous shocks have on the commuting experience and, hence, the inferred VoT. Our focus is not on the multi-tasking activities on a commuter trip but on the effect of reduced commuting and greater take up of WFH on the VoT. Working from Home (WFH) is a response, voluntary or forced initially on a significant part of a population with seismic implications for the commuting trip, which has been either totally curtailed or undertaken at a far lesser rate per week than before the COVID-19 pandemic. With many views on what the future may or may not look like as we move out of the COVID-19 period and start to see a 'new normal', one thing is becoming more certain, which is that the quantum of weekly commuting is likely to change substantially with fewer people travelling to a regular workplace on any one day (see Beck and Hensher 2021).

The other literature that had gained a lot of traction and support pre-COVID-19 relates to the stability of travel time budgets for specific activities. Stopher, Ahmed, & Liu (2017), for example, investigated the idea of stability of travel time budgets using GPS data collected for 29 Australian households over a period of eight years. Their results show that there seems to be an average travel time expenditure of around one hour per person per day. There were, however, significant differences in the levels of travel time expenditure, with 55% of the sample having an average within ±15 minutes from the mean. Milakis, Cervero, van Wee, & Maat (2015) investigated the acceptable threshold for commuting travel times using open and closed-ended interview questions on a sample of 30 persons in Berkeley, USA.

Their results show that there was a negative satisfaction for zero minutes commute time, which represents telecommuting, and trips of 30 minutes or longer. Respondents said they disliked telecommuting when asked about the hypothetical zero commute time, suggesting that the ideal commute time is around 18 minutes.

As interesting as these results may appear, it is increasingly unlikely that the evidence can be used to inform circumstances that have arisen as a result of the COVID-19 pandemic which is much more severe and global in its impact, changing the whole fabric of society in terms of its view and preferences on travel and WFH. Additionally, it is important to again state that the impact of COVID-19 is not to completely replace the office with WFH, but rather has the aforementioned potential to change the number of commuting trips that would be required in a "new" average week, and thus how a commuter may evaluate those fewer trips that they might make. While it might be too early to claim any sense of a stable predictable 'new normal', we believe that the current circumstance is sufficiently different to the pre-COVID-19 era for regular modal commuting that it is timely, and appropriate, to ask if the mean VoT may be different to what was anticipated and recommended in guidelines back in 2019.

From ancillary questions we have the following evidence of the way in which any change in available time and money due to reduced commuting and increased WFH has been used. 57% of the sample in the GSMA responded yes to the question "Since you started working from home, do you think you are saving money in an average each week, by commuting less (or not at all)?". Also, in response to the question 'In the short-term, what are you doing with the money that you are no longer spending on commuting?', 79% said they save it, with no current plans to spend it on anything; 10% indicated saving for a specific activity such as a holiday, and 11% indicated that they are now spending the money on something else already. On time allocation, in response to a question 'Thinking about working from home and the time you save from not commuting, how much of that time do you spend working versus using it for other activities that do not involve work?', 32 percent on average (33 percent standard deviation) was spent doing additional work that was paid for, 22 percent on average (25 percent standard deviation) was spent doing additional work that was not paid for, and 46 percent on average (standard deviation of 34 percent) was spent on leisure or family activities in the GSMA area[8]. What this suggests is that the reallocation of time and money between work, commuting and leisure as a consequence of increased WFH appears to result in a mix of increased working time and increased leisure time, in lieu of reduced time spent commuting. While we have not been able to find any statistically significant influence of these responses on the VoT associated with commuting (see later model results), they provide informative evidence on how realised changes in time and money spent on commuting is used.

3. Descriptive Overview of the Data used to obtain Revised Estimates of VoT

The data used in this paper is part of a larger study on the impact of working from home on commuting and non-commuting travel activity (see Beck and Hensher 2020, 2020a, and Beck et al. 2020). Full Details of the sample and the overall longitudinal approach is given in Beck and Hensher (2021) in which some respondents are in multiple waves and other respondents are in a single wave, with approximately 50% being workers, where a worker is defined as anyone who was working at least 1 day prior to COVID-19 restrictions. Data was collected in a series of Waves from March 2020 with the

[8] The percentages can be related to average travel times and cost outlays given in Table 2, typically 60 minutes for car and 80 minutes for public transport per day.

current data in Wave 3 collected in September 2020[9]. The online survey company PureProfile was hired to randomly sample respondents and surveys were available across Australia. Quotas were not introduced on those completing the survey, other than ensuring representation from all states and territories. Given the focus on New South Wales and Queensland (as the funding sources), we have a larger sample of over 1,000 interviews per State with the data used in this paper on workers drawn from the Greater Sydney Metropolitan Area (GSMA).[10]

We have used the subset of observations of individuals who had paid work before and during the COVID-19 pandemics and who have a regular place of employment when they commute, since our focus is on gaining an appreciation of the extent to which the preferences of commuters have changed as they have increasingly, to varying degrees, experienced WFH and hence changed the pattern and frequency of commuting to a given work location outside of the home.

The profile of respondents' characteristics as well as the descriptive profile of the alternative's attribute levels are presented in Table 1. For the GSMA (metropolitan area of New South Wales, NSW) we have 409 respondents (after data cleaning), which for the commuter mode choice model is a total of 11,328 observations given that for each respondent we have 7 days of the week and four times of day[11]. The modal choice sets also vary according to the perceived availability of each mode (Table 3). The modal attributes are summarised in Table **2**[12]. The main differences in travel times are by bus, ferry and bicycle which are much higher than the other modes.

Table 1: Descriptive profile of respondents - mean (standard deviation)

Variables	**GSMA**
Age	39.18 (12.2)
Average personal annual income (AUD$000)	90.21(60.4)
Number of people in the same house	2.83 (1.3)
Number of cars in your household	1.53 (0.9)
Number of children in household	1.77 (1.0)
Number of modes available	2.92 (1.4)
Proportion who used car as driver to commute prior to COVID-19	0.510
Distance from home to regular workplace location (kms)	22.28 (29.5)
Proportion of sample who are blue collar workers	0.078
Proportion who have a high level of concern number of people in PT	0.575
Occupation professional (1,0)	0.375
Occupation manager (1,0)	0.176
Occupation sales (1,0)	0.072
Occupation clerical and administration (1,0)	0.236
Occupation community and personal services (1,0)	0.072
Occupation technology (1,0)	0.053
Occupation machine operators (1,0)	0.007

[9] Data collection is a continuing activity with another four surveys throughout 2021 and beyond until there is evidence of a stable relationship between travel and WFH.

[10] The GSMA includes Newcastle, Sydney, Central Coast, Illawarra, Nowra-Bomaderry, St Georges Basin-Sanctuary Point, Milton-Ulladulla, and Kangaroo Valley-Southern Highlands.

[11] There are 42 ToD/DoW periods representing 10 modes for each of the four times of day plus now work and WFH. Each DoW is a separate observation which is why we controlled for the potential correlation between observations over 7 days common to each respondent.

[12] The attributes were obtained from modal choice sets obtained from each respondent but were subject to extensive checking using postcode information of home and work location to ensure that reported (i.e. perceived) levels of times and costs (tolls, in-vehicle fuel and fares) etc. were validated with the levels in aggregated networks and other sources such as google travel times. This was a significant task to ensure that what we are using is indeed reliable perceived levels but not levels that we would deem are outliers.

Variables	GSMA
Occupation labourers (1,0)	0,0180
NSW - Wollongong residential location (1,0)	0.097
NSW - Newcastle residential location (1,0)	0.101
NSW – Central Coast residential location (1,0)	0.109
Work located in CBD (1,0) (postcodes = 2000, 2007, 2009 and 2011)	0.245
Number of respondents	**409**

Table 2: Mode attributes - mean (standard deviation) for one-way trips

Variables	GSMA
Travel time car driver (min)	29.73 (28.3)
Travel time car pax (min)	28.48 (23.3)
Travel time taxi/ride share (min)	26.44 (26.5)
Travel time train (min)	37.20 (37.8)
Travel time bus (min)	47.21 (41.7)
Travel time light rail (min)	28.64 (21.1)
Travel time ferry (min)	33.00 (23.7)
Travel time walk (min)	52.71 (38.9)
Travel time bicycle (min)	50.68 (62.6)
Travel time motorcycle (min)	26.50 (20.1)
Fuel car driver (AUD$)	2.61 (3.4)
Fuel car pax (AUD$)	2.48 (2.6)
Fuel motorcycle (AUD$)	2.91 (3.0)
Parking car driver (AUD$)	4.60 (13.7)
Parking car pax (AUD$)	2.49 (11.6)
Parking motorcycle (AUD$)	3.00 (7.1)
Toll car driver (AUD$)	1.46 (4.6)
Toll car pax (AUD$)	0.98 (3.8)
Toll motorcycle (AUD$)	1.38 (3.6)
Waiting time taxi/ride share (min)	10.35 (8.2)
Waiting time train (min)	8.68 (6.5)
Waiting time bus (min)	10.69 (8.0)
Waiting time light rail (min)	6.43 (4.6)
Waiting time ferry (min)	16.10 (12.1)
Egress time taxi/ride share (min)	3.34 (8.2)
Egress time train (min)	13.47 (14.9)
Egress time bus (min)	10.19 (12.9)
Egress time light rail (min)	9.57 (10.7)
Egress time ferry (min)	14.30 (17.2)
Access time taxi/ride share (min)	9.94 (16.5)
Access time train (min)	22.04 (24.7)
Access time bus (min)	21.40 (30.1)
Access time light rail (min)	19.71 (19.0)
Access time ferry (min)	23.10 (12.8)
Ride Share fare ($)	40.54 (69.8)
Train Fare ($)	5.56 (5.2)
Bus Fare ($)	4.40 (3.4)
Light Rail Fare ($)	4.13 (2.7)
Ferry Fare ($)	4.14 (2.4)

Although our focus is on estimating a traditional commuter mode choice model enhanced by measures to assess the influence of the number of weekly days working from home in particular on VoT, we provide in Table 3 the shares of commuting trips by 10 modes, No Work and WFH across seven days of the week for four times of day[13]. As expected, many times of day and days of the 7-day week involve no formal paid work (35.1%); in contrast we see that of the ToD/DoW periods, 26% involved working from home (out of 68.9% who reported were able to WFH), with 38.9% involving a commuting trip to a location outside of the home. This has significant implications on the quantum of commuting activity on any one day of the week and time of day, and if maintained post-COVID-19 is expected to have a massive impact on the performance of the transport network. There has been a greater decline in public transport trips compared to car travel linked to the biosecurity risk, real or otherwise in using public transport, and hence the increased dominance of the car in the commuter modal share.

Table 3: Modal availability and shares in the presence of WFH and No Work for each day of week and time of day

		GSMA area count	GSMA area %
Availability	No Work	409	100.0%
	WFH	282	68.9%
	Car driver	293	71.6%
	Car passenger	141	34.5%
	Taxi/ride share	122	29.8%
	Train	192	46.9%
	Bus	214	52.3%
	Light rail	28	6.8%
	Ferry	10	2.4%
	Walking	105	25.7%
	Bicycle	65	15.9%
	Motorcycle	26	6.4%
Number of respondents			***409***
Choices	No Work	993	35.1%
	WFH	735	26.0%
	Car driver	750	26.5%
	Car passenger	61	2.2%
	Taxi/ride share	7	0.2%
	Train	120	4.2%
	Bus	67	2.4%
	Light rail	11	0.4%
	Ferry	2	0.1%
	Walking	54	1.9%
	Bicycle	16	0.6%
	Motorcycle	16	0.6%
Number of respondents			***409***

Table 4 differs from previous tables in that it summarises the key attributes that we investigated in arriving at the final preferred model used to obtain the overall average VoT and the VoT segments by the number of days over a 7-day period working from home. Specifically, we investigated a number of interactions between travel time, WFH (linear and quadratic), personal income (linear and quadratic), occupation and concern over using public transport, as well as conditioning the one-way trip travel time of the proportion of travel time outlaid per week during COVID-19 compared to before. We also investigated interacting income with cost as multiplicative and by division. The final models,

[13] The times of day are 7am to 8.59am, 9am to 2.59pm, 3pm to 5.59pm and 6pm to 6.69am, which are consistent with the GSMA transport authority strategic models.

presented below, finally settled on interactions between travel time, the quadratic of WFH, the inverse of personal income and a linear interactions of travel time with a dummy variable for managers and professionals, and a dummy variable for high bio-security concern in using public transport.

Table 4: Attribute profiles - mean (standard deviation)

Attribute	Mean (std deviation)
One-way trip travel time (minutes)	36.172 (33.83)
One-way trip travel time * Number days WFH	77.312 (137.50)
One-way trip travel time (min) * Personal income '00,000 ($AUD)	29.898 (8.55)
Number days WFH	1.878 (2.19)
(Number days WFH)^2	8.306 (11.05)
One-way trip travel time * (Number days WFH)^2	342.699 (671.40)
One-way trip travel time (min) *Manager/Professional dummy variable	19.838 (31.06)
One-way trip travel time (min) *High level of concern about public transport dummy variable	0.448 (0.497)
Car/motorcycle cost: fuel + toll + park per one-way trip (AUD$)	7.995 (17.16)
Public transport one-way trip fare (AUD$)	10.944 (17.22)
Commuting weekly travel time pre-COVID (min)	151.805 (194.50)
Commuting weekly travel time post-COVID (min)	129.619 (163.29)
Commuting weekly cost pre-COVID (AUD$)	28.326 (73.28)
Commuting weekly cost post-COVID (AUD$)	22.179 (56.82)
Before - during COVID weekly commuting travel time	22.186 (127.07)
Before - during COVID weekly commuting cost	6.147 (36.29)
One-way trip travel time * TT post-COVID/TT pre-COVID	17.705 (28.65)
Weekly number of days worked post-COVID	4.707 (0.96)
Weekly number of days worked pre-COVID	4.405 (1.24)
Weekly number of days WFH post-COVID	1.878 (2.19)
Weekly number of days WFH pre-COVID	0.738 (1.51)
Number of days WFH/Total worked days post-COVID	0.158 (0.32)
Number of days WFH/Total worked days pre-COVID	0.404 (0.46)

4. Methodology

The mode choice model has 40 alternatives, which represent the mode that the respondent used to go to work and the time of day they left their house (ToD). Each day is separated into four time-of-days (ToDs) used, which are consistent with the GSMA transport authorities' strategic model: AM peak: 7-9 am, Inter-peak: 9 am - 3 pm, PM peak: 3 pm - 6 pm, and Evening: 6 pm - 7 am[14]. The different alternatives and their description are presented in Table 5.

[14] These times of day are the ones used by Transport for NSW and hence we used them in the GSMA model.

Table 5: Alternative description

Alternative	ToD	Mode	Alternative	ToD	Mode
1	-	No work	22	2	Motorcycle
2	-	Work from home	23	3	Car passenger
3	1	Car driver	24	3	Car passenger
4	1	Car passenger	25	3	Taxi/rideshare
5	1	Taxi/rideshare	26	3	Train
6	1	Train	27	3	Bus
7	1	Bus	28	3	Light rail
8	1	Light rail	29	3	Ferry
9	1	Ferry	30	3	Walk
10	1	Walk	31	3	Bicycle
11	1	Bicycle	32	3	Motorcycle
12	1	Motorcycle	33	4	Car driver
13	2	Car driver	34	4	Car passenger
14	2	Car passenger	35	4	Taxi/rideshare
15	2	Taxi/rideshare	36	4	Train
16	2	Train	37	4	Bus
17	2	Bus	38	4	Light rail
18	2	Light rail	39	4	Ferry
19	2	Ferry	40	4	Walk
20	2	Walk	41	4	Bicycle
21	2	Bicycle	42	4	Motorcycle

We added the interaction over all modes between travel time and the combined occupations of management and professional, as well as an interaction between travel time and concern about biosecurity (as a proxy for crowding an health risk) in the four public transport modal alternatives.

The utility functions for the mode choice model are described by two types of alternative specific constants: one that refers to mode *m*, and one that refers to the time-of-day *t*. The utility function for the public transport modes (including rides share) is defined by travel time TT_{Mode_m} as a main effect which is mode-specific[15] and estimated as random to account for preference heterogeneity, and as a mode-generic interaction with the inverse of annual personal income $PInc$[16], the number of days working from home, the latter expressed as a quadratic effect $WFHd$, a dummy variable for managers and professionals $MgrProf$, and a dummy variable representing a high level of concern over using public transport *ConPT*; access time AcT_{Mode_m}; egress time EgT_{Mode_m}; waiting time WT_{Mode_m} and fare $Fare_{Mode_m}$, as shown in equation (1). The parameter estimate β for access, egress and waiting times is generic[17]. The βs represents the estimated parameters associated with the different attributes or characteristics.

[15] This standalone parameter is later considered common between public transport and car, but different to the active modes.
[16] We began by relating income to cost but could not get a statistically significant relationship as either a ratio or a product. By relating income to travel time we are recognising that individuals with varying incomes have different marginal dis-utilities associated with levels of travel time.
[17] They were estimated as specific first and the results suggested that they were not statistically different.

$$U_{Mode_m,ToD_t}^{PT} = ASC_{Mode_m} + ASC_{ToD_t} + (\beta_{TT,Mode_m} + \beta_{TT,PInc} / Pinc + \beta_{TT,WFH} \cdot WFHd^2 \\ + \beta_{TT,\text{MgrProf}} \cdot Mgr\,\mathrm{Pr}\,of + \beta_{TT.ConPT} \cdot ConPT) \cdot TT_{Mode_m} \\ + \beta_{Cost,Mode_m} \cdot Fare_{Mode_m} + \beta_{TTAEW} \cdot \left(AcT_{Mode_m} + EgT_{Mode_m} + WT_{Mode_m} \right) \tag{1}$$

The utility function for the car driver and motorcycle alternatives is described by travel time, by itself as a main effect estimated as random to account for preference heterogeneity and also as an interaction with the inverse of personal income and number of days WFH squared, as in the public transport modes, as well as a dummy variable for managers and professionals; fuel cost $Fuel_{Mode_m}$; parking cost $Park_{Mode_m}$; and toll costs $Toll_{Mode_m}$. Different respondents' socioeconomics were tested in different modes of transport, but in addition the inclusion on occupation and income interacted with WFH), only the number of cars per person in household was statistically significant in the car driver mode (as Z_n). Note that the parameter estimate β for fuel, toll and parking was estimated in the preferred model as generic[18]. For the car passenger alternative, cost was excluded since the evidence supported only the driver incurring that cost.

$$U_{Mode_m,ToD_t}^{Car/moto} = ASC_{Mode_m} + ASC_{ToD_t} + (\beta_{TT,Mode_m} + \beta_{TT,PInc} / Pinc + \beta_{TT,WFH} \cdot WFHd^2 \\ + \beta_{TT,\text{MgrProf}} \cdot Mgr\,\mathrm{Pr}\,of) \cdot TT_{Mode_m} \\ + \beta_{Mode_m,Cost} \cdot \left(Fuel_{Mode_m} + Park_{Mode_m} + Toll_{Mode_m} \right) + \sum_n \beta_{Mode_m,n} \cdot Z_n \tag{2}$$

The quadratic form provides a well-known way of establishing whether there is a non-linear relationship, in our case, between the VoT and the #days WFH. This is of greater interest than simply identifying a relationship between VoT and WFH per se. We also investigated the role that modal switching between pre-COVID-19 and during COVID-19 might play but could not find any statistically significant effects for each and every modal pair. Mackie et al. (2003) suggest that when income is associated with a function for travel time (or trip length) that 'Making further allowance for income variation introduces some complications because of the potential interdependence between income and journey length.' We investigated this before finalising the model form, and found that the partial correlation between personal income and travel time was very low, namely -0.03736.

It is important to note the difference between the mode-specific random parameter associated with travel time, $\beta_{TT,Mode_m}$ and the mode-generic fixed parameter associated with the interaction of travel time and the inverse of income, $\beta_{TT,PInc}$. The first one, $\beta_{TT,Mode_m}$ represents the differences in the value of public transport and car travel time relative to active modes, and it also represents the unobserved preference heterogeneity in the value of public transport and car modes (as this parameter was estimated as random). The second parameter, $\beta_{TT,PInc}$, represents observed heterogeneity in the value of travel time (across all modes) explained by the income level of the respondent.

5. Results

The final mixed logit model is summarised in Table 6. It was selected after extensive consideration of alternative preference expressions for a one-way single trip travel time and travel cost, personal income, the number of days per week WFH, occupation and bio-security concern in using public transport, with random and fixed parameters. We also conditioned travel time on the change in the proportion of weekly travel time outlay before and during COVID-19, as well as the absolute

[18] They were estimated as specific first and the results suggested that they were not statistically different.

difference, but they did not improve on the overall model performance and we suspect this is because the presence of the number of days WFH provided a better representation of the change in weekly travel time associated with the period during COVID-19. Also, we suspect that any time budgets pre-COVID-19 have been greater than during COVID-19 or at least not reached, and hence the use of the number of days WFH is a very good proxy for the impact of allocations of time and cost to commuting.

Overall, the model is statistically very good, with an impressive Pseudo-R^2 of 0.5 with constants and 0.36 excluding constants, with all parameter estimates, excluding the alternative-specific constants, being statistically significant at 90% or better. The random parameters were estimated as a constrained normal distribution, setting the standard deviation of travel time to 1.28 of the mean and the standard deviation of cost to 0.9 of the mean[19]. This is an appropriate way to identify the extent of preference heterogeneity which is often poorly captured by unconstrained distributions. 1,000 intelligent (Halton) draws were used and observations that are common within each respondent were accounted for using a panel form of the likelihood expression.

The majority of the parameter estimates are generic across the alternatives where that attribute is included. Initially we investigated mode-specific parameter estimates and found that the improved statistical fit and significance of particular parameter estimates gravitated to a generic specification, notably in-vehicle travel time and cost. While this is not uncommon in many models, this may be reflective of the way in which the commuter trips are viewed during COVID-19, where the focus is more on whether to commute or not instead of WFH, and hence a downgrade of the differences in modal choice (with the exception of bio-security risk) within this setting. Some attributes such as access, egress and wait time are associated with subsets of modes such as public transport and are treated as generic and aggregated across all available public transport modes. The marginal disutility is lower than the in-vehicle parameter; however, the travel variable has a generic parameter across car and public transport. A possible explanation is linked to the significant drop in use of public transport (reduced to less than 50% of the pre-COVID-19 levels) and hence there is less sensitivity to these travel time components. The inclusion of walking and bicycling is important during COVID-19 since these modes have grown in popularity as the main commuting mode, and hence have a renewed role in the overall estimate of the commuter VoT.

In addition to socioeconomics influence of personal income, we identified the number of cars per adult in a household to be positive and statistically significant in the car driver utility expression; suggesting, as expected, that as the number of cars per adult in a household increases, the probability of commuting by car as a driver increases. The usual mode-specific constants are included, but we have also added in time-of-day of trip commencement constants for three of the four times of day. All other influences being held constant, we see that the contribution to the overall marginal (dis)utility of an alternative is greatest during the peak period compared to the inter-peak and the evening; hence there is a time of day deflation effect partially offsetting the marginal disutility contribution of travel time and cost for trips undertaken during the peaks compared to other times of day.

It is important to also point out that we have modelled a seven-day week in contrast to the five-day week, since we know from our surveys that an increasing number of workers chose to WFH on the weekend which prior to COVID-19 would have occurred at the office during the 5-day week, consistent with an increasing flexibility in work. Thus, any analysis of the relationship between commuting and

[19] Extensive estimation was undertaken to ensure that the number of draws and constraints on the normal distribution provided very stable estimates under repeated draws. We also undertook analysis with constrained and unconstrained triangular distributions and in willing to pay space and found similar results.

WFH must include all seven days, recognising this greater flexibility that is available when working from home. Separately, although our focus is not on demand predictions, the use of a typical daily trip prediction expanded up to a week, month, or any period must be qualified since we no longer can talk about a simple number of average weekly trips under the now observed distribution of the number of days WFH.

Table 6: Mixed logit model parameter estimates

Parameters	Acronym	Alternatives	Mean (t value)
ASC car driver/motorcycle (1,0)	ASC_CarMoto	1, 10, 11, 20, 21, 30, 31, 40	2.963 (4.40)
ASC car passenger (1,0)	ASC_CarP	2, 11, 22, 32	0.865 (1.68)
ASC taxi/ridesharing (1,0)	ASC_Taxi	3, 13, 23, 33	-0.913 (1.11)
ASC public transport (1,0)	ASC_PT	4-7, 14-17, 24-27, 34-37	1.418 (2.07)
ASC active modes (1,0)	ASC_Act	8, 9, 18, 19, 28, 29, 38, 39	0.792 (1.22)
ASC ToD 1 and 3 (AM and PM peak) (1,0)	ASC_T13	1-10, 21-30	0.578 (6.01)
ASC ToD 4 (Evening after 6pm) (1.0)	ASC_T4	31-40	0.375 (3.39)
Car driver - Number of cars per adult in household	NCar_CarD	1, 11, 21, 31	0.492(3.75)
Travel time (minutes) all modes except active - *mean*	TT_CarPT	1-7, 10-17, 20-27, 30-37, 40	-0.016 (2.04)
- *standard deviation*			0.020 (2.04
Interaction with inverse of personal income '00,000 ($AUD)	TT/PInc	1-7, 10-17, 20-27, 30-37, 40	0.007 (3.09)
Interaction with number days WFH squared	TT_WFH²	1-7, 10-17, 20-27, 30-37, 40	-0.007 (1.97)
Interaction with Managerial & Professional occupation (1,0)	TT_MgrProf	1-7, 10-17, 20-27, 30-37, 40	0.016 (2.06)
Interaction with High level of concern about Public Transport	TT_ConsPT	4-7, 14-17, 24-27, 34-37	-0.013 (-2.12)
Travel time walking (minutes)	TT_Walk	8, 18, 28, 38	-0.035 (3.24)
Travel time bicycle (minutes)	TT_Bike	9, 19, 29, 39	-0.073 (1.97)
Cost ($) all modes except car pax and active - *mean*	Cost_CarPT	1, 3-7, 10, 11, 13-17, 20, 21, 13-27, 30, 31, 33-37, 40	-0.063 (3.18)
- *standard deviation*			0.063(3.18)
Access + egress + waiting time taxi/PT modes (minutes)	TTAEW	3-7, 13-17, 23-27, 33-37	-0.008 (1.98)
Number of parameters estimated			15
Sample size			831
Log Likelihood at convergence			- 1,517.68
Log likelihood at zero			- 3,065.46
Log likelihood at constants only			-2,355.31
McFadden Pseudo R squared (without constants)			0.51 (0.36)
AIC/n			3.70

The particular focus of this paper is on the VoT. The formula extracted from the estimated model is given in equation (3) expressed in $/person hour, with *rna* the constrained normal distribution and $sd\beta$ the standard deviation beta profile for a random parameter, with the other notation as before. The form of VoT is obtained as the ratio of the marginal disutility of travel time to travel cost. The Marginal (dis) utility of WFH is 2* $\beta_{TT,WFH} \cdot WFHd$ (the derivative of travel time with respect to WFDd). The same logic applies to personal income.

$$VoT = 60 * \frac{\begin{pmatrix} ((\beta_{TT} + rna \cdot sd\beta_{TT}) + 2 \cdot \beta_{TT,WFH} \cdot WFHd + \beta_{TT,PInc} \cdot \left[1/(PInc)^2 \right] \\ + \beta_{TT,\mathrm{MgrProf}} \cdot Mgr\,\mathrm{Pr}of + \beta_{TT.ConsPT} \cdot ConsPT)) \end{pmatrix}}{\left(\beta_{Cost} + rna \cdot sd\beta_{Cost} \right)} \tag{3}$$

The VoT expression is the mean over the joint distribution of the random parameters in the utility specification as shown in Table 6, with the random coefficients being independently distributed. Since there are random coefficients appearing in both the numerator and denominator of equation 3, the expression is an approximation for the true mean. The key findings are presented in Table 7 for each segment of days WFH as well as a weighted average across the number of days WFH. The sign of the relationship between WFH and VoT is clear: the higher the higher (positive) VoT is proven empirically by the parameter TT_WFH2, which has just passed the threshold of significance. The statistically significant sign for the interaction between one-way trip travel time and the square of #days WFH suggests that, ceteris paribus, the more days someone works from home, the greater the marginal disutility of a commuting trip's travel time and this changes as the number of days increases and the positive sign for the interaction between travel time and personal income, the latter divided into travel time, suggests that as personal income increases, ceteris paribus, the lower the marginal utility effect which results in a smaller reduction in the overall marginal disutility of travel time.

Holding travel time constant, the positive parameter on professional and managerial occupation suggests a reduced marginal utility of travel time, which may seem surprising given that these occupations typically have higher incomes; however, it is the impact of both the income and WFH interactions with travel time and the occupation dummy variable that contribute to the resulting VoT. We also see a negative parameter for concern over using public transport suggesting, ceteris paribus, contributing to a lower VoT. The sign of the latter is interesting since it is far from obvious as to what direction that influence could have taken. However the inclusion vs exclusion of the occupation dummy variable and concern about public transport did not noticeably influence the mean VoT across all days of week WFH. When excluding these two interactions, the overall mean estimate is $25.15 per person hour compared to $25.53 per person hour. Hence, as the return to public transport slowly increases (being at 85% in Sydney in March 2021), as well as some switch back to public transport away from the car, we do not expect this to result in a noticeable change in the mean VoT as long as the distribution of days WFH remain.

The overall mean estimate for the VoT is $25.53 per person hour[20] with a distribution from a low mean estimate of $20.39 for individuals who do not work from home at all (i.e., commute 5-7 days a week), to a high mean estimate of $36.95 per person hour for individuals who WFH five to seven days a week but still might commute a small amount (Table 7 and Figure 4[21]). Hence, the more days someone works from home in a week, *ceteris paribus*, the more they value a unit of commuting travel time. This suggests that our initial hypothesis appears to be borne out by the empirical evidence; namely, that reduced weekly commuting activity means that an individual is willing to pay more to save time on a single trip simply because they commute less and hence have more travel budget to spend to maximise the utility of commuting, as well as being less sensitive to travel outlays including delays (i.e., a higher threshold). All else being equal, if the same total travel budget is now being allocated over a reduced number of trips, the willingness to pay per trip would increase.

With an estimate of VoT obtained during COVID-19, the logical next issue is to ask whether this is different to the mean estimates used and/or recommended by government planning agencies before COVID-19. In the Australian context for the GSMA, Transport for NSW appraisal guidelines recommend $17.72 for the value of travel time savings per person hour (TfNSW 2020, page 10), which is based on very little working from home (less than 4%) and hence the appropriate comparator VoT is for zero days WFH, or $20.39. Our mean estimate differs from the TfNSW recommended value, that appears to be an update based on an assumption that private travel time is valued at 40 per cent of the seasonally adjusted full time Average Weekly Earnings (AWE) for Australia, assuming a 38-hour

[20] This overall the VoT of $25.53 per person hour at the 95% confidence interval varies from $9.04 to $41.77 per person hour given a standard error of $8.45.

[21] The standard errors of the estimates and the confidence intervals were obtained using the Delta method (see Hensher et al. 2015, Chapter 7.4, pp340-351). This is an appropriate method when interest is in variances of function and willingness to pay.

working week, and assumed to be applicable for the private car, motorcycle, bicycle, walking and public transport for commuting and recreational trip purposes. No distinction was made between congested and non-congested travel time conditions in terms of parameter estimates, which is also the situation during COVID-19, although it is clear that traffic congestion on the roads overall was lower at the time of the survey. Importantly, this government recommended estimate includes non-commuting trips and hence a commuting specific VoT is expected to be greater than this recommended value, with the $20.39/person hour being quite reasonable.

To obtain a pre-COVID-19 estimate, we have to make a number of assumptions. In particular we need to use the distribution of days WFH in 2019 from the same sample (shown in Table 7) and also hold personal income and other socio-economic contextual variables fixed at the current level. Importantly we are using a 7-day week and not a 5-day week and hence the somewhat higher incidence of WFH. We also assume that the preference for a unit of travel time and cost only varies between the two periods due to the changing mix of incidence of commuting and WFH.[22] Given these assumptions, $22.69 per person hour seems eminently reasonable for the pre-COVID-19 reference value. With a mean VoT of $25.53 per person hour during COVID-19, when we weight the mean estimates for each of the number of days WFH by the incidence of such days pre- and during COVID-19, it is 12.55% higher than the pre-COVID-19 estimate.[23]

This evidence suggests that the use of pre-COVID-19 mean estimates of VoT must be questioned as being an under-estimate of what commuters are, on average, willing to pay to save time when they are increasingly relating the utility of the commuting trip to the opportunity to work from home. What is especially pleasing is that the evidence from a model in which we did not interact travel time with the number of days working from home for commuting modal alternatives, but included alternatives for WFH and No Work, produces a mean estimate of VoT of $26.02 per person hour with a range at the 95% confidence interval of $9.17 to $42.85 (Hensher et al. 2021a). We can be very confident that during COVID-19 and beyond, if WFH is maintained to some extent at a level greater than pre-COVID-19, the mean estimate of the commuting VoT is likely to be higher than before COVID-19.

Table 7: Mean Estimates of VoT Overall and #Days WFH

	Proportion Days WFH		**VoT ($/person hour) Mean (lower and upper bounds)**
# Days WFH	Pre-COVID-19	During COVID-19	During COVID-19
0	0.6844	0.4899	20.39 (7.3-39.2)
1	0.113	0.0693	23.15 (8.4-40.1)
2	0.0684	0.0829	25.91 (9.1-40.9)
3	0.039	0.06	28.67 (9.5-41.5)
4	0.0163	0.0714	31.4 (10.2-42.2)
5	0.0729	0.1954	34.19 (10.5-43.6)
6 plus	0.006	0.0311	36.95 (12.2-46.9)

[22] The distribution of travel times and costs pre- and during COVID-19 are very similar for the majority of the sample, and while the mean travel time and cost was higher pre-COVID-19 (see Table 4), the majority of the sample had levels of time and cost during COVID-19 that were contained in the greater part of the pre-COVID-19 distribution (See Appendix A).

[23] Wages grew 1.4% over the year to September quarter 2020 (https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/wage-price-index-australia/latest-release), but inflation was 0.7% (https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/consumer-price-index-australia/sep-2020); hence a minimal difference could reasonably be expected at the individual level.

Weighted average	VoT ($/person hour)
Pre-COVID-19	22.69
During COVID-19	25.53
Percent increase	*12.55*

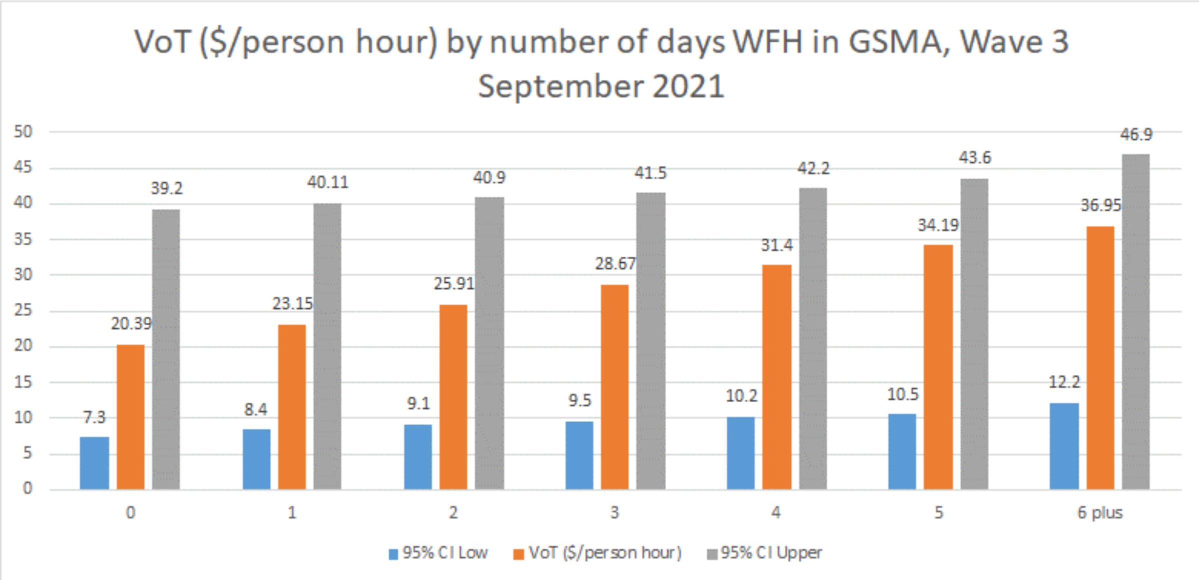

Figure 4: Distribution of the VoT for Days WFH, with upper and lower limits of 95% confidence interval

6. Conclusions

This paper has investigated how the value of time might change during the COVID-19 pandemic when there is a sudden and significant shock resulting in a noticeable reduction in the amount of commuting activity accompanied by a sizeable increase in working from home. Regardless of whether the incidence of working from home will subside to some extent or completely post COVID-19, whenever that is likely to be, we need to assess and reassure ourselves that key economic parameters still have numerical credibility.

With travel time being the most influential attribute in the identification of user benefits in transport appraisal, it is beholden on us to establish the case for maintaining or changing the mean estimates of the value of time (in $/person hour) in order to ensure that we are better informed on its role in the future under what many have described as a 'new normal' without a return to the patterns of past preferences and behaviour.

This paper was motivated by the desire to investigate the possibility of a revision in the VoT. We began by promoting a view that the mean VoT may be different (higher or lower) than prior to COVID-19, for a number of reasons including the change in the incidence of commuting as WFH increased over a week, as well as an accompanying revision of the way in which travel time and travel cost, in particular, are assessed under a revised set of preferences now that much of commuting activity can be avoided (including the bio-security risk of using public transport), changing the view of time and money budget thresholds and the marginal value of a unit of travel time when there is less time and cost outlaid over a week. Theory suggests that constraints on the goods-leisure trade off will change dramatically, and indeed this appears to be the case.

The most important finding from this study is that not only does the mean estimate of the VoT appear to be higher by 12.55% compared to pre-COVID-19, but that the mean estimate is higher for individuals who opt for a higher number of days WFH, and hence reducing the impost of the commute. Individuals appear to be willing to pay more to save a unit of commuting travel time when they undertake less frequent trips. The logic is very plausible and aligns with evidence in other contexts that less frequent trips for a given a trip purpose, tend to have a greater willingness to pay for a specific level of service. We also found in Hensher et al. (2021a) that individuals who live further from their normal workplace and, hence, have a longer commuter trip, also tend to work from home more days a week, and by evidence have a higher VoT. A 12.55% increase has huge implications on the economic benefits of transport initiatives, and for many large roads and public transport infrastructure projects where commuting activity is hundreds of millions of hours per annum, the dollar value of increased user benefits will be significant, and likely change the prioritisation of investments where the evidence of benefit-cost analysis is used in decision making.

Like any research effort there are always caveats. After extensive modelling in this paper and in Hensher et al. (2021), additional segments to account for occupation and industry (beyond the important distinction for managers and professionals) will be of interest although we doubt this will influence the overall message, given what we have found to date. It will, however, enable practitioners to further adjust the evidence to allow for this additional composition of the working population since we know that many occupations and industries have varying degrees of capability to be able to WFH given the essential nature of many jobs that require a face-to-face presence. We have focussed on commuting (between home a regular office location), and in other research we have recognised that reduced commuting activity associated with increased WFH results in some amount of increased non-commuting activity. In ongoing research, we are investigating the implications of this change on the VoT of non-commuting activity, accounting for the changing spatial context in which many of these trips are now taking place, especially in a more local setting closer to home. In addition, it will be interesting to investigate further the extent to which direction causality might lead to antagonistic interpretations of what will happen if WFH becomes more prevalent in society. Specifically (1) WFH influences VoT will cause the VoT to *increase* at the margin, because more WFH makes people value travel time higher (more negatively). (2) WFH influenced by VoT will cause the VoT to *decrease* at the margin, because the share of travellers with low WFH suggest a low Value of leisure time will increase. Finally, we acknowledge that behaviour in the post-COVID-19 (or more likely referred to as 'living with COVID-19') world is currently unknown. However, we do know that many people have adopted WFH and there are clear signals that WFH will continue to a greater extent in the future than before. The impacts of this for ongoing research are two-fold. Firstly, transport agencies should continue to monitor how values of time have changed and/or continue to change during COVID-19 to provide better insight for future disruption, and equally this research should be ongoing into the long-term as we do not yet know if the budgetary allocation of time or money as it pertains to commuting will remain the same into the long-term or be reallocated to other expenditure, changing the constraints and thus the calculus once more.

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Appendix A. Kernel density estimate for travel time and cost pre and post-COVID-19.

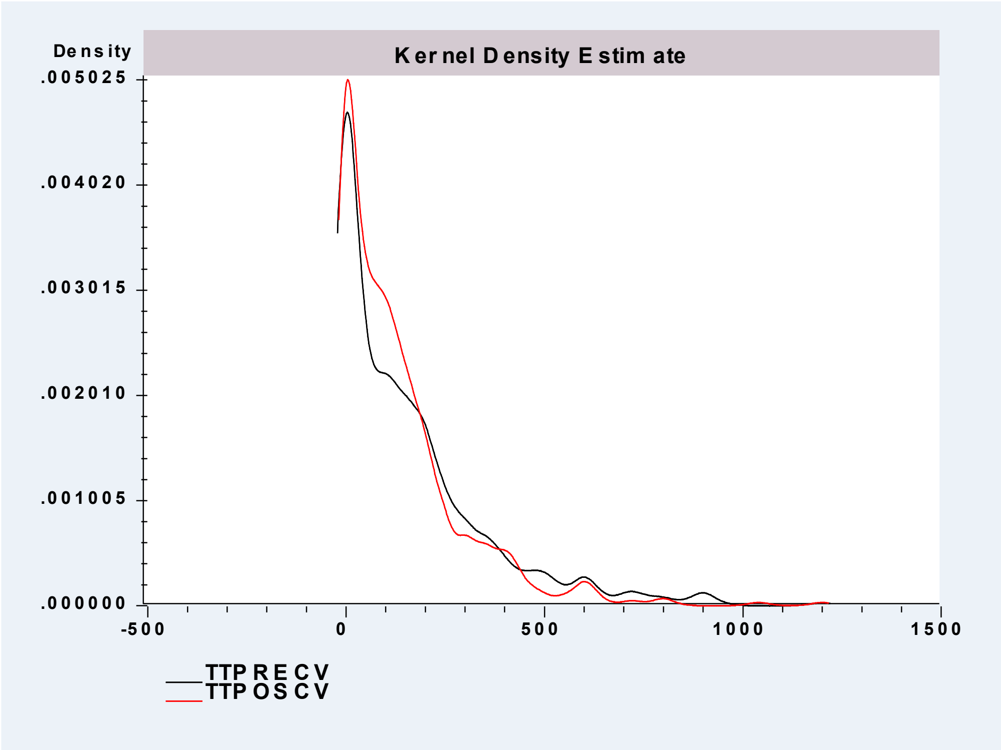

Figure A1: Travel time pre-COVID-19 (TTPRECV) and during COVID-19 (TTPOSCV)

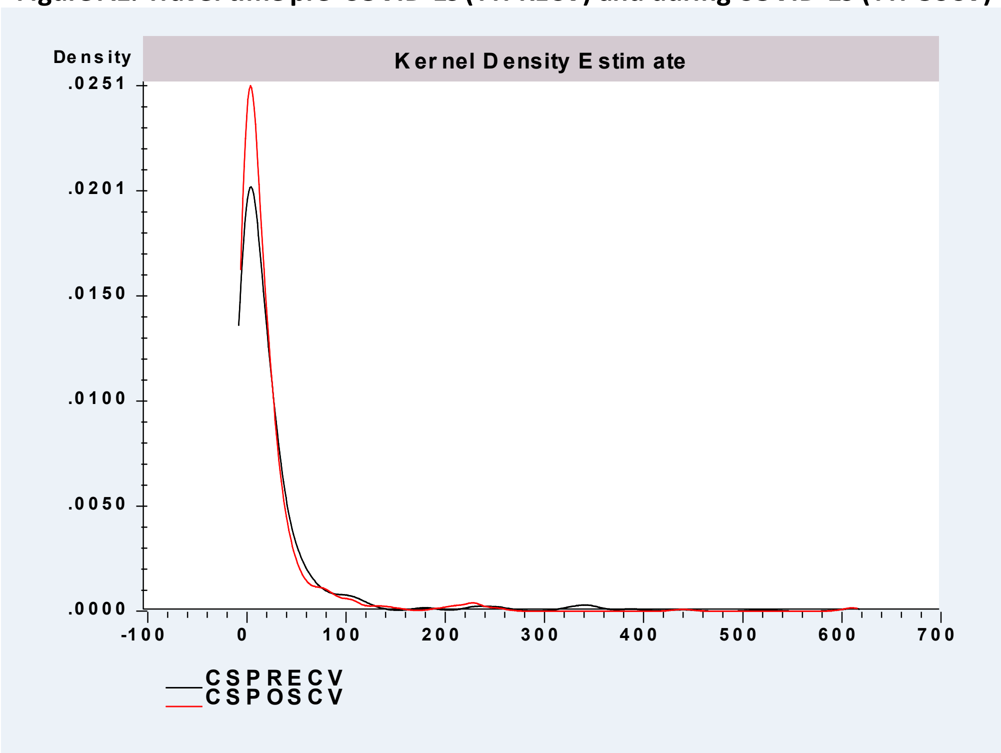

Figure A2: Travel cost pre-COVID-19 (CSPRECV) and during COVID-19 (CSPOSCV)

Appendix B. Recognising the impact of constraints under a growing incidence of WFH and reduced commuting activity per time period.

Consider a regular commuting activity involving 10 one-way trips each week, which requires an allocation of time and money. An individual will choose the modal alternative that provides the greatest amount of utility or satisfaction, given the individual's preference for mixtures of travel time and cost in line with the time and money budget that have made available for consumption in the commuting activity. With reduced commuting activity due to increased time spent working from home, we can expect a revision of the binding nature of the time and money constraints that will, in turn, influence the value of time for such activity. This context can be embedded within the theory of the allocation and valuation of travel time, under which an individual consumes time and goods.

The realisation that time is a scarce resource which affects the demand for market goods and services, just like the allocation of scarce money resources, suggests that time is an important input in consumption activities. It is also a factor in production activity (i.e., work). The use of time in 'non-productive' activities thus involves an opportunity cost that must be valued. Theories of time allocation form a natural framework within which to derive a theoretical measure of VoT. Key ideas are presented below with more detail in many sources, especially contributions in more recent times by Jara Diaz (1998, 2000, 2007) and Jara Diaz and Candia (2020).

Time can be viewed as a commodity because it can generate utility directly to the individual when 'consumed' in specific activities. But at the same time, it also acts as a *means for the consumption* of market goods and services, just as money is a means for the purchasing (and hence, consumption) of these goods and services. In its role as a commodity, time in a specific activity *i* is not the same commodity as time in another activity *j*. Consider the following model in (A1) after DeSerpa (1971). The individual's utility function can be expressed as:

$$U = U\left(x_1,\ T_1;\ x_2,\ T_2;\ \ldots;\ x_n,\ T_n\right) \tag{A1}$$

where $\{T_1, \ldots, T_n\}$ is the time spent in activities 1 to *n*, and $\{x_1, \ldots, x_n\}$ is market goods and services consumed jointly with time in the *n* activities. 'Commodities' denote market goods and/or services and/or time inputs into activities, the latter defined in terms of inputs rather than 'output'. In its role as a means for the consumption of goods and services x_i's, time is subject to a resource constraint of T (or time budget):

$$\sum_{i=1}^{n} T_i \le T \tag{A2}$$

Similarly, the means for purchasing the x_i's, at price p_i's, are also subjected to a resource constraint of M (or monetary budget):

$$\sum_{i=1}^{n} p_i \cdot x_i \le M \tag{A3}$$

Time consumption in many activities a_i is not entirely a matter of an individual's own free will. In addition to the time-resource constraint (A2), there are time consumption constraints:

$$T_i \ge a_i \cdot x_i;\ i = 1,\ \ldots,\ n \tag{A4}$$

These constraints include technological and institutional constraints. Examples of technological constraints are the available set of transport modes that have limits on the combinations of travel times and costs that can be offered. An example of an institutional constraint is the legal speed limit. The application of microeconomic theory recognises these limits imposed on a solution to the value of transferring time (Truong and Hensher 1985).

This model has the following characteristics. The level of utility is dependent on the consumption of all goods and on the time assigned to all activities including work, unlike Becker (1965; see also Evans 1972). There are time and income constraints, and the latter includes a variable work time that generates income through a wage rate; there are exogenous minimum time restrictions for travel and fixed work, and endogenous ones for all the other activities, that depend on goods consumption.

To establish the trade-off between time and price, we have to define the consumer's optimisation problem as that of maximising utility subject to the time and money resource constraints and the time consumption limit, as follows:

$$L = U\left(\underset{\sim}{X},\, T\right) + \mu\left(\mathrm{T}^0 - \sum_i \mathrm{T_i}\right) + \lambda\left(M - \sum_i \mathrm{p_i} \cdot \mathrm{x_i}\right) + \sum_i \kappa_i \cdot \left(\mathrm{T_i} \geq \mathrm{a_i} \cdot \mathrm{x_i}\right) \qquad \text{(A5)}$$

We use the Lagrange Multiplier (L) to specify the objective function and the set of three budget and time consumption constraints. The theoretical interpretation of the Lagrange multipliers within the framework of non-linear programming, establishes that they correspond to the variation of the objective function evaluated at the optimum due to a marginal relaxation of the corresponding restriction. This way, the multiplier μ associated with the time restriction is the marginal utility of time representing by how much utility would increase if individu al time available was increased by one unit. Equivalently, λ is the marginal utility of income and κ_i is the marginal utility of saving time in the i^{th} activity.

The first order conditions for maximum utility are required to establish the marginal rate of substitution between time and money, noting that $\partial U/\partial z$ is the marginal utility of attribute z:

$$\begin{aligned}
&\frac{\partial U}{\partial x_t} = \lambda \cdot \mathrm{p_i} + \kappa_\mathrm{i} \cdot \mathrm{a_i} \\
&\frac{\partial \mathrm{U}}{\partial \mathrm{T_i}} = \mu - \kappa_i \\
&\frac{\partial \mathrm{U}}{\partial \mathrm{M}} = \lambda \\
&\kappa_\mathrm{i} \cdot \left(\mathrm{T_i} - \mathrm{a_i} \cdot \mathrm{x_i}\right) = 0
\end{aligned} \qquad \text{(A6)}$$

To derive the value of travel time we divide the second condition by the third condition:

$$\frac{\partial U/\partial \mathrm{T_i}}{\partial U/\partial \mathrm{M}} = \frac{\mu - \kappa_\mathrm{i}}{\lambda} \qquad \text{(A7)}$$

From the interpretation of the multipliers, three concepts of time value were defined by DeSerpa (1971): the value of time as a resource for the individual (μ/λ); the value of saving time in the i^{th}

activity (κ_i $/\lambda$); and the value of assigning time to the i[th] activity $((\partial U/\partial T_i)/\lambda)$. The last two definitions are activity specific while the first is not. Also, the value of assigning time to an activity is the money value of the direct marginal utility. Beyond these definitions, one can add the marginal price of assigning time to an activity which, in the case of work, would correspond to minus the marginal wage (Gronau 1986). The value of saving time in the i[th] activity will be zero if the individual voluntarily assigns to it more time than the required minimum (which is how DeSerpa defined a leisure activity)[24]. It will be positive otherwise. This means that the individual will be willing to pay to reduce the time assigned to a certain activity only if he is constrained to assign more time to it than desired.

To establish a relation between the different concepts of time value, the first order conditions in (A6) can be manipulated to obtain a result originally established by Oort (1969).

$$\frac{\partial U/\partial \mathrm{T}_W}{\lambda} = \frac{\partial U/\partial \mathrm{T}_\mathrm{i}}{\lambda} \qquad \text{(A8)}$$

This expression shows that the value of saving time in the *i[th]* activity is equal to the value of doing something else minus the value of assigning time to that particular activity because it is being reduced. Equation (A8) improves over Becker (1965), for whom time was valued at the wage rate (W), and over Johnson (1966), for whom the value of time was μ/λ. For those activities that are assigned more time than the minimum required ($\kappa_i = 0$, a leisure activity), the value of assigning time $(\partial U/\partial T_i)/\lambda$ is equal to μ/λ for all of them. This is the reason why DeSerpa called it the value of leisure. On the other hand, μ/λ is also equal to the total value of work, which has two components: the money reward (the wage rate) and the value of its marginal utility. Therefore, the value of saving time in a constrained activity is equal to the value of leisure (or work) minus its marginal utility value (presumably negative). Jara-Diaz (2000, 2008) presents the details.

If we consider the particular case of travel, it can be shown that the value of saving travel time, κ_i/λ, corresponds exactly to the ratio between the marginal utilities of time and cost that are estimated as part of the modal utility in a discrete travel choice model. This has been shown in different forms by various authors (Bates 1987, after Truong and Hensher 1985, Jara-Díaz 1998, 2008). Although empirical values for K_i/λ can be estimated using the discrete travel choice framework (as in the current paper), no methodology has been developed to estimate all of the different elements in equation (A8) from a model system. The best antecedent is Truong and Hensher's (1985) effort at obtaining μ/λ as part of the coefficient of travel time in mode choice models (which they claim was μ/λ- K_i/λ), which prompted Bates' (1987) identification of that coefficient as κ_i/λ only.

There is nothing in this theoretical framework that should differ with reduced commuting activity other than the empirical nature of the degree to which particular constraints are binding and the

[24] The value of *saving* time in an activity is the willingness to pay to reduce that activity. If the individual assigns voluntarily more time than the minimum required, she is not willing to pay to reduce it precisely because the value of the marginal utility is positive (what De Serpa called the value of time assigned to the activity). See (2.42) in Jara Diaz (2007) where the value of saving time is the expression on the left hand side, and the value of time assigned is the value of the marginal utility (far right term). Thus, if the individual assigns more time than needed, the multiplier K_j is zero and the value of the marginal utility is (positive and equal for all activities whose κ_j is nil). Discussions with Sergio Jara Diaz are appreciated.

value of κ_i/λ might change. Working from home is simply a reallocation of time between commuting and other activities of which the main ones are increased working time and leisure time. Hence, we might expect a different empirical value of travel time savings, due in large measure, we hypothesise, to the availability of additional time to reallocate to non-commuting activities with T_i and x_i, i= commuting, reduced per period of time. In general, if there is a change in U from reallocation of commuting time to another activity$_i$: $(\mu_{commute}/\lambda) > \lambda_i/\lambda$ and the value of time saving on commuting is expected to increase. If the change in U is from a reallocation of the commuting budget to another spend$_i$: $(\kappa_{commute}/\lambda) > \kappa_i$, then value of time savings for the commute trip is expected to decrease. If the value of time is constant, we can expect a proportional change in μ and κ_i such that value of time stays in equilibrium. The final result is empirical.