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The impact of working from home on modal commuting choice response during COVID-19: Implications for two metropolitan areas in Australia

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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. Not only does this change the performance of the transport network, it also means that the way in which transport modellers and planners use models estimated on a typical weekday of travel and expand it up to the week and the year must be questioned and appropriately revised to adjust for the quantum of working from home. Although teleworking is not a new phenomenon, what is new is the ferocity by which it has been imposed on individuals throughout the world, and the expectation that working from home is no longer a temporary phenomenon but one that is likely to continue to some non-marginal extent given its acceptance and revealed preferences from both many employees and employers working from home makes good sense. This paper formalises the relationship between working from home and commuting by day of the week and time of day for two large metropolitan areas in Australia, Brisbane and Sydney, using a mixed logit choice model, identifying the influences on such choices together with a mapping model between the probability of working from home and socioeconomic and other contextual influences that are commonly used in strategic transport models to predict demand for various modes by location. The findings, based on Wave 3 (approximately 6 months from the initial outbreak of the pandemic) of an ongoing data collection exercise, provide the first formal evidence for Australia in enabling transport planners to adjust their predicted modal shares and overall modal travel activity for the presence of working from home.

1. Introduction

Working from Home (WFH) is evolving into a popular and potentially significant alternative to commuting to a regular office location. We have described it as the most influential transport policy lever that we have seen since World War II (Hensher et al. 2020), with evidence from many jurisdictions suggesting a preference for WFH at least 1 or 2 days a week (Beck and Hensher 2020a, Barralo et al. 2021). To the surprise of many commentators, both employees and employers have adapted extremely well to forced WFH with many advantages (and some disadvantages) being revealed. Most notable has been the amount of trust demonstrated by employers for
employees to WFH (at least to some extent going forward) linked to increased productivity, and employees seeing WFH as an opportunity to reduce the stress of commuting and opening up greater quality time with family and friends, especially when aligned with more flexible working hours (Beck and Hensher 2020, 2020a, 2021a, 2021).

Given the growing evidence that WFH is unlikely to be a temporary phenomenon¹, the need to review current transport models that are used to obtain predictions of commuter modal choice and aggregate modal shares becomes of paramount importance. With reduced commuting activity each day of the week and a move to greater flexibility in the time of day and day of week that employees work (extending beyond weekdays to include weekends and evenings throughout the week), as well as a growing preference for staggered working hours, there is a need to reconsider (at least) commuter mode choice models. A reconsideration of the commuter mode choice model must now allow for the real possibility of replacing a regular commuting trip (for a fixed number of days per week in most cases), with working from home, as well as not working at all at particular times of the day, across days of the week, while attaining the agreed number of weekly working hours. Crucially, we suggest that a commuter mode choice model must recognise the role of WFH and No-Work in establishing the probability of commuting on a particular day and at a particular time of day by a specific mode from the full set of modes including walking and bicycle, given that the latter two active modes have grown in relevance (Beck and Hensher 2020a).

In developing new empirical models of commuter mode choice in the context of WFH, this paper draws on data collected in the third wave, called Wave 3, of an ongoing COVID-19 Travel Survey which went into field from the 4th of August the 10th of October, approximately 6 months after the beginning of the pandemic.² We focus on two metropolitan areas in South East Queensland (including Brisbane) (SEQ), and the Greater Sydney Metropolitan Area (GSMA), presenting formal discrete choice models of commuting versus working from home or not working at all for specific days of the week and times of day. Details of the data collected for all of Australia in Wave 3 as well as the previous waves has been presented in detail in Beck and Hensher (2020, 2020a, 2021), Beck et al. (2020), and Hensher et al. (2020, 2021)³. The data collected is extensive, but in this paper we focus on summarising only the descriptive evidence relating to working from home in Wave 3 as a prelude to the presentation of the model forms used and the sampled profile of commuter mode choice and available modes.

The paper is organised as follows. In the next section we provide a brief literature review given that much of the material has been summarised and commented on in Beck and Hensher (2020, 2020a) and Beck et al. (2020) which list many of the main contributions by other authors. We then provide a descriptive profile of the context within which we are modelling the choice between WFH and commuting. We then set out the mixed logit model form together with the definitions used for the alternatives in the commute mode choice versus WFH and No-Work model. A descriptive profile of the relevant data is presented followed by the model results for each of SEQ and GSMA. The next section sets out the mapping model between the probability of WFH and a number of socio-demographic variables and contextual characteristics as a way of providing a practical tool to predict the incidence of WFH in various population and location segments; with a number of simulated applications presented. The paper concludes with a summary and suggested ongoing research activity.

2. Literature review on working from home in the commuting context

Working from home has long been of interest to transport researchers. In early work the focus was mainly on white collar workers in the information technology sector (Salomon and Salomon 1984), and many looked barriers which might exist to working from home such as lack of social interaction, inability to separate home from work, and feeling that there was a need to be seen in order to advance (Salomon 1986, Hall 1989). Nonetheless, the concept of working from home gained traction in the transport literature as a relatively fast and inexpensive way to overcome several problems associated with congestion and it was argued that the impact of telecommuting on traditional transport demand models needed to be considered (Mokhtarian 1991).

Ben-Akiva et al. (1996) proposed a travel demand modelling framework for the information era. They outline a three-stage approach to incrementally updating the forecasting process through understanding how lifestyle decisions impact on mobility choices and how both impact on daily activity patterns. While Ben-Akiva et al. (1996) include sampling of both employees and employers, Yen and Mahmassani (1997) include both from the same organisation. The role of social influence and social contact on telecommuting has also been explored (Wilton et al. 2011). Recent studies that have explored the relationship between the choice and frequency of telecommuting and characteristics of the individual, household, job type and built environment include Sener and Bhat

¹ Unlike the influence of previous pandemics and natural disasters which, in the main, have been very localised and had limited impact on work activity.
² The data collected to date since early 2020 has three waves. While Wave 1 was collected to ensure as complete a replication of Australian socio-demographics as possible, the focus of Wave 2 and Wave 3 was to create a valuable time-series of cross-sections ‘panel’ data set (typically rare in transportation research), where a percentage of the repeated sample was the same individuals, designed to ensure representation from all states and territories. The impact of COVID-19 is, however, sufficiently widespread that no demographic can escape the disruption caused. The ongoing plan is to analyse Waves 2 and 3 with subsequent waves, with Wave 4 having been collected in June 2021. We will be estimating models along the exact same lines as the Wave 3 models developed in this paper where we see the current paper as the first representation of a new model form that provides an appealing framework within which to condition out the probability of working from home and non-working over a 7 day week in order to adjust for the future incidence of commuting activity.
³ We also used the Wave 2 survey instrument to undertake surveys in South America and South Africa. See Vallejo-Borda et al. (2021) for the South American study and Balbontin et al. (2021) for both South America and South Africa.
In terms of the effect of telecommuting on travel behaviour, Mokhtarian et al. (1995) found that both commute and non-commute travel (measured in person-miles) decreased as a result of telecommuting. Mokhtarian et al. (2004) found that one-way commute distances were longer for telecommuters than for non-telecommuters, but average commute miles overall were less than non-telecommuters due to trip infrequency. Hensher and Golob (2002) updated the current thinking on the role of the interaction between telecommunications and travel which at the time was described as ‘the opportunity to appraise the potential for telecommunications to facilitate and/or enhance the exchange of information with/without travel’. Zhu (2012), however, found that telecommuting generated longer one-way commute trips but also longer and more frequent daily total work trips and total non-work trips, arguing that there is in fact a significant complementary effect of telecommuting on personal travel. Research by Kim et al. (2015) also found that telecommuting can indeed be a complement, particularly when it releases the household vehicle from mandatory work travel, to be used for non-commute trips.

However, in Australia the incidence of working from home remained persistently low, the Australian Household Income and Labour Dynamics survey (DSS 2020) shows that over the duration of the survey, which first commenced in 2001, approximately 25% of respondents worked from home regularly at an average of 11 h per week. In exploring barriers to working from home, Hopkins and McKay (2019) find that it was a managerial decision rather than a function of the type of work that suppressed uptake. Such barriers are also prevalent in precarious and unskilled areas of the economy which have restricted access to flexible work practices (van den Broek and Keating 2011). There are other inequities in working from home, such as differences in outcomes for employed women and men with children, particularly in the areas of job satisfaction and satisfaction with the distribution of childcare tasks (Troup and Rose 2012); whereas other have found some evidence that working from home contributes to better relationships and a more equitable division of household responsibilities for couples with children (Dockery and Bawa 2019). With regards to COVID-19 it has been found that the impact has been disproportionately large on women (Nash and Churchill 2020, Craig and Churchill 2020, Lister 2020).

In April 2020, Linkedin developed the Workforce Confidence Index (Anders 2020), which shows that in Australia almost a quarter of respondents stated they felt safer at home, and another quarter would not want to go back to back to full-time office based employment. As a result of COVID-19, it may be possible that we will see the rise in working from home that was anticipated in the early work as far back as the 1970’s. Should this indeed be the case, then there are significant ramifications for future travel demand and the model systems on which demand forecasts are made. For example, in the context of Sydney, the Strategic Transport Model (STM) is the primary tool used to test alternative settlement and employment scenarios; and determine the travel demand impacts from proposed transport policies, transport infrastructure or services. Many of these tools do not consider working from home in any significant way, as prior to COVID-19 working from home was not systematic.

3. Descriptive overview of working from home in Wave 3 (August-September 2020)

We provide a brief assessment of the reported evidence on the impact of working from home on travel activity in the SEQ and GSMA areas for workers in Wave 3, excluding all non-workers from the analysis. We refer the reader to a more extensive discussion in Beck and Hensher (2020a, 2020b) and Beck et al. (2021)\(^4\), Vallejo-Borda et al. (2021) and Balbontín et al. (2021) have recently reported on the evidence from five South American Cities. The evidence presented in this section uses the sample that is the basis of the estimation of the mixed logit model in a following section.

With regards to the number of days worked, the dashed line in Fig. 1 indicates that there has been a slight downturn in Wave 3 compared to before COVID-19 in both the GSMA and SEQ. Prior to COVID-19 there were no reported differences in the average number of days worked by males and females, however in Wave 3 females reported a significantly lower number of days worked in the last week. Older and lower income respondents worked less days in an average week both prior to COVID-19 and in Wave 3. Conversely, as shown in Fig. 2, we see across the board growth in working from home in both the GSMA and SEQ; from an average of 0.9 days before COVID-19 to 1.6 during Wave 3. However, the average number of days worked from home in the GSMA (1.8 days) is significantly higher than the number in the SEQ (1.4 days). Males in the GSMA work more days from home on average than others, as do higher income respondents in both the GSMA and SEQ.

As highlighted in Fig. 3, the growth in work from home is due to workplaces either giving employees the choice to work from home or directing them to do so (50% in the GMSA and 45% in SEQ). In the GSMA, males are more likely to be directed to work from home whereas females are more likely to be in employment where work cannot be done from home. In both the GSMA and SEQ, higher income respondents are more likely to be given the choice or directed to work from home whereas lower income respondents are typically less able to work from home due to the nature of their work. With regards to any shift in the workplace policy around working from home, Fig. 4 shows that the growth in working from home is also likely coming from respondents who had the ability to work from home prior to COVID-19 but are doing so more often during Wave 3 than they did before. Again, higher income respondents are

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\(^4\) Beck and Hensher (2021, 2021a) summarise the status of the pandemic at the time of the Wave 3 survey in Australia. On the 2nd of August, metropolitan Melbourne moved into stage-four lockdowns, being only allowed to shop for food and necessary supplies within 5 km of their home, exercise for one hour once per day within 5km of home, and a stay-at-home curfew from 8:00pm to 5:00am each night. At approximately the same time, regional Victoria was placed in stage-three “stay at home” restrictions. In other states, New South Wales continued to experience low levels of community transmissions, primarily linked to an outbreak in South-West Sydney that was the result of a function at a hotel/bar attended by a COVID-19 positive guest who had travelled up from Melbourne for the event. Elsewhere in Australia, COVID-19 had been all but eliminated save for returning travellers.
more likely to belong to this group.

With regards to the day of the week that respondents work from home, Fig. 5 shows a relatively even spread over the course of the typical working week in both the GSMA and SEQ, albeit at a higher rate in the GSMA. This is a non-trivial point; for the benefits of reduced commuting behaviour to be maximised, demand needs to be reduced by some margin on each day to improve traffic flow, rather than having all of the benefits of a reduction limited to one or two days (and likely a case where the reduction on these days is large but fails to add any additional marginal benefit than that which would accrue at a smaller fall in commuting).

When asked about the days a respondent would like to work from home in the future once COVID-19 restrictions cease, a similarly uniform distribution is observed (Fig. 6). Interestingly, the number of days an employee would like to work from home in the future in the GSMA is the same as the current levels observed during Wave 3; but for SEQ the average number of days an employee would like to work from home in the future is significantly higher than is currently the case in the Wave 3 collection period. Younger and middle-aged respondents, along with those on middle to higher incomes, would like to work from home significantly more than others.

It comes as no surprise that working from home is more of an option for different occupations and is more prevalent in certain industries. Fig. 7 shows that the white-collar occupations of managers, professionals, technicians and trades, and clerical and
administration all exhibit a higher average number of days worked from home\textsuperscript{5}. Fig. 8 shows that working from home is lower in occupations that require some focal point service delivery and retail\textsuperscript{6}.

With regards to how respondents travel to work, the majority of respondents indicated that the car (as driver) was their main mode for commuting before COVID-19 (see Fig. 9). The dominance of car has increased as in both the GSMA and SEQ the number of respondents reporting the car as the main mode has increased in Wave 3. On the other hand, we see a decline in the train as the reported main mode (particularly in the GSMA) and slight decreases in the bus.

The downturn in public transport use and the increase in the car as the main mode for commuting is likely attributable to the concern that people have about biosecurity in public transport and overcrowding in the context of the requirement to social distance. In Wave 3, the concern around both issues continues to remain very high, as shown in Fig. 10, with more than half of respondents in the GSMA and SEQ reporting moderate to extreme concern about the hygiene of public transport and numbers of other people using public transport. Concern is significantly higher on average in the GSMA across both dimensions. Females also express significantly higher concern in both the GSMA and SEQ, as do older respondents in SEQ, with both hygiene and numbers of people using public transport.

Overall, these results indicate that even six months after the initial outbreak of COVID-19 in Australia (around mid-March 2020), working from home continues to exist in a significant way at levels much higher than before COVID-19. Given that working from home remains a viable tool for authorities to reduce movement and thus potential contagion, along with helping to alleviate potential congestion particularly in the increasing dominance of the private vehicle (something that many jurisdictions globally have fought

\textsuperscript{5} Occupations are coded as per the ABS Australian and New Zealand Standard Classification of Occupations \url{https://www.abs.gov.au/ausstats/abs@.nsf/mf/1220.0}

\textsuperscript{6} Industries are coded as per the ABS Australian and New Zealand Standard Industrial Classification \url{https://www.abs.gov.au/ausstats/abs@.nsf/mf/1292.0}. In the analysis industries are further grouped into broad categorisations that are used within transport authority modelling, specifically: Retail (wholesale trade, retail trade, accommodation and food services); Service (education and training, health care and social assistance, arts and recreation services, other services); Professional (financial and insurance services, rental hiring and real estate services, professional, scientific and technical services, administrative and support services, public administration and safety); Industry (manufacturing, construction, transport, postal and warehousing, information media and telecommunications); and Other (agriculture, forestry and fishing, mining, electricity, gas, water and waste services).
hard to erode), encouraging working from home to continue would be desirable outcome for authorities and society. The descriptive analysis herein indicates that respondents would like to continue to do so, at levels that are higher than before COVID-19. It should be noted that neither we nor any authority should expect working from home to be an all or nothing proposition, rather simply more working from home than was the case before COVID-19 would have positive dividends.

There is broad evidence that increased levels of working from home is likely to continue into the future. A recent report from KPMG
finds that flexible working is quickly becoming a key element of the employee value proposition and will contribute to an organisation’s ability to attract and retain talent. Others find that as a result of experiences during COVID-19, a majority of workers want more flexibility when it comes to remote work and interest is actually higher among managers than general employees (Hennessy 2020). A large study of 6,000 respondents within the community and public sector found that 90% of managers reported staff productivity to be the same or higher whilst working from home and nearly two-thirds saying they intended to be more supportive of working from home in the future (Colley and Williamson 2020).

The Australian evidence aligns well with a recent USA study by Barrero (2021) who surveyed more than 30,000 USA residents over multiple waves in 2020 to investigate whether WFH will stick, and why. That found that 20 percent of full workdays will be supplied from home after the pandemic ends, compared with just 5 percent before [COVID-19], 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 (Beck and Hensher 2020, 2020a; Beck

(KPMG 2020)
et al. 2020). 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.

4. Methodology

The model structure used in this study is presented in Fig. 11. Respondents were asked, for each day of the week, where they worked from and, if they went outside the home to work, at what time of day and what mode of transport they used. There were three main alternatives for each day: not work, work from home (WFH) only, work outside home at some point during the day. The possible alternatives are defined by four different times of day (ToD) and ten modes of transport available: car driver, car passenger, taxi/rideshare, train, bus, light rail, ferry, walk, bicycle, and motorcycle. This model structure includes 42 alternatives that are presented in Table 1, and the ToDs for QLD and NSW are defined in Table 2. Different ToD specifications were considered for each state (NSW and QLD) so that they are aligned with the definitions used by the relevant transport authorities (Transport for NSW (TfNSW) and Transport and Main Roads Queensland (TMR), respectively), which are different across states.

The alternative of no work (alternative 1) is described by the alternative specific constant ASC and by respondents’ socioeconomics zn. The working from home alternative (alternative 2) is described by its alternative specific constant; respondents’ socioeconomics; by dummy variables that represent each different day of the week d; and by the distance from their home to their office DistHome-work. The utility functions are defined as follows:

\[
U_{\text{NoWork}} = \text{ASC}_{\text{NoWork}} + \sum_n \beta_{\text{NoWork}, n} \cdot z_n \tag{1}
\]

\[
U_{\text{WFH}} = \text{ASC}_{\text{WFH}} + \sum_n \beta_{\text{WFH}, n} \cdot z_n + \sum_n \beta_{\text{WFH}, d} \cdot d + \beta_{\text{WFH,CBD}} \cdot \text{CBD}_{\text{work}} + \beta_{\text{WFH,Dist}} \cdot \text{DistHome-work} \tag{2}
\]

where \( \beta \) represents the estimated parameters associated with the different attributes or characteristics. The utility functions for the modal alternatives (alternatives 3 to 42) are described by two 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 is defined by travel time \( TT_{\text{Mode}_n} \), access time \( Act_{\text{Mode}_n} \), egress time \( EgT_{\text{Mode}_n} \), waiting time \( WT_{\text{Mode}_n} \), and fare \( Fare_{\text{Mode}_n} \), as shown in equation (3). Note that the parameter estimate \( \beta \) for access, egress and waiting times is generic7.

\[
U_{\text{PT}}^\text{Mode}_n, \text{ToD}_t = \text{ASC}_{\text{Mode}_n} + \sum_n \beta_{\text{Mode}_n, TT} \cdot TT_{\text{Mode}_n} + \beta_{\text{Mode}_n, Cost} \cdot Fare_{\text{Mode}_n} + \beta_{\text{Mode}_n, AEW} \cdot (Act_{\text{Mode}_n} + EgT_{\text{Mode}_n} + WT_{\text{Mode}_n}) \tag{3}
\]

The utility function for the car driver and motorcycle alternatives is described by travel time, fuel cost \( Fuel_{\text{Mode}_n} \), parking cost \( Park_{\text{Mode}_n} \), and toll costs \( Toll_{\text{Mode}_n} \), as well as some socioeconomic characteristics8, as presented in equation (4). Note that the parameter estimate \( \beta \) for fuel, toll and parking was estimated in the preferred model as generic9.

\[
U_{\text{Car/moto}}^\text{Mode}_n, \text{ToD}_t = \text{ASC}_{\text{Mode}_n} + \sum_n \beta_{\text{Mode}_n, TT} \cdot TT_{\text{Mode}_n} + \beta_{\text{Mode}_n, Cost} \cdot (Fuel_{\text{Mode}_n} + Park_{\text{Mode}_n} + Toll_{\text{Mode}_n}) + \sum_n \beta_{\text{Mode}_n, n} \cdot z_n \tag{4}
\]

The active modes and car passenger10 alternatives are described only by the travel time, as presented in Eq. (5).

\[
U_{\text{Active}}^\text{Mode}_n, \text{ToD}_t = \text{ASC}_{\text{Mode}_n} + \sum_n \beta_{\text{Mode}_n, TT} \cdot TT_{\text{Mode}_n} \tag{5}
\]

Looking ahead to the results, we find that the role of travel time and travel cost changes quite noticeably when WFH and not working are allowed for. With a significant number of days WFH in particular (see Fig. 2), typically 1 to 2 days per week, the incidence of commuting declined noticeably (especially for public transport), and as a consequence the sensitivity to daily travel time and cost is expected to change. We suggest there is likely to be less sensitivity to travel time and cost given that the weekly outlays are reduced, resulting in the value of travel time savings (VoT) that could be higher or lower than before COVID-19. We hypothesise a higher VoT if one is prepared to pay more per trip since there are less outlays required per week given the time and money budgets; but lower with

7 They were estimated as specific first and the results suggested that they were not statistically different.
8 The respondents’ socioeconomics were tested in different modes of transport, but they were statistically significant only in the car driver mode.
9 They were estimated as specific first and the results suggested that they were not statistically different.
10 We tested the option of including the costs associated with a car trip but they were always not significant, suggesting that car passengers do not usually pay for these costs and, therefore, are not part of their decision.
Table 1
Alternative numbers per DoW.

| Alternative | Description | Monday - Sunday | Description | Monday - Sunday |
|-------------|-------------|-----------------|-------------|-----------------|
| 1           | Not work    |                 | 22          | Work outside home ToD 2 - motorcycle |
| 2           | Work from home only |                 | 23          | Work outside home ToD 3 - car driver |
| 3           | Work outside home ToD 1 - car driver |                 | 24          | Work outside home ToD 3 - car passenger |
| 4           | Work outside home ToD 1 - car passenger |                 | 25          | Work outside home ToD 3 - taxi/rideshare |
| 5           | Work outside home ToD 1 - taxi/rideshare |                 | 26          | Work outside home ToD 3 - train |
| 6           | Work outside home ToD 1 - train |                 | 27          | Work outside home ToD 3 - bus |
| 7           | Work outside home ToD 1 - bus |                 | 28          | Work outside home ToD 3 - light rail |
| 8           | Work outside home ToD 1 - light rail |                 | 29          | Work outside home ToD 3 - ferry |
| 9           | Work outside home ToD 1 - ferry |                 | 30          | Work outside home ToD 3 - walk |
| 10          | Work outside home ToD 1 - walk |                 | 31          | Work outside home ToD 3 - bicycle |
| 11          | Work outside home ToD 1 - bicycle |                 | 32          | Work outside home ToD 3 - motorcycle |
| 12          | Work outside home ToD 1 - motorcycle |                 | 33          | Work outside home ToD 4 - car driver |
| 13          | Work outside home ToD 2 - car driver |                 | 34          | Work outside home ToD 4 - car passenger |
| 14          | Work outside home ToD 2 - car passenger |                 | 35          | Work outside home ToD 4 - taxi/rideshare |
| 15          | Work outside home ToD 2 - taxi/rideshare |                 | 36          | Work outside home ToD 4 - train |
| 16          | Work outside home ToD 2 - train |                 | 37          | Work outside home ToD 4 - bus |
| 17          | Work outside home ToD 2 - bus |                 | 38          | Work outside home ToD 4 - light rail |
| 18          | Work outside home ToD 2 - light rail |                 | 39          | Work outside home ToD 4 - ferry |
| 19          | Work outside home ToD 2 - ferry |                 | 40          | Work outside home ToD 4 - walk |
| 20          | Work outside home ToD 2 - walk |                 | 41          | Work outside home ToD 4 - bicycle |
| 21          | Work outside home ToD 2 - bicycle |                 | 42          | Work outside home ToD 4 - motorcycle |

Table 2
QLD and NSW ToD combinations available.

| ToD | QLD time frames | NSW time frames |
|-----|-----------------|-----------------|
| 1   | 7am to 8.59am   | 7am to 8.59am   |
| 2   | 9am to 3.59 pm  | 9am to 2.59 pm  |
| 3   | 4 pm to 5.59 pm | 3 pm to 5.59 pm |
| 4   | 6 pm to 6.69am  | 6 pm to 6.69am  |
relatively less congestion on the roads and also willing to put up with any delays when they occur given it is associated with fewer days per week of commuting.

5. Descriptive profile

The profile of respondents’ characteristics included in the models, as well as the descriptive profile of the alternative’s attribute levels are presented in Table 3. For the GSMA (metropolitan area of New South Wales, NSW) we have 409 observations (after data cleaning), which for the commuter mode choice model is a total of 40,735 observations that represent the different available alternatives for each DoW-respondent (plus commuting alternative). For the SEQ (metropolitan area of Queensland, QLD) we have 247 respondents’ observations representing for the modelling 24,393 observations for different available alternatives for each DoW and ToD-respondent and commuting alternative.

The GSMA and the SEQ data have a similar age, number of people in the same household, and number of modes available. However, the average personal annual income in the GSMA area is higher, the number of cars in the household is slightly smaller, and there are slightly more children per household.

The modes’ characteristics are presented in Table 4. The main differences in travel times are by bus, ferry and bicycle which are much higher in the GSMA area. These variables are included in the models presented in the following subsection.

The shares of commuting mode, No Work and WFH for SEQ and GSMA are shown in Table 5. As expected, many times of day and days of the 7-day week involve no formal paid work; in contrast we see that of the 42 ToD/DoW periods, 19.6 and 26% percent involved working from home, with 46% and 39% respectively for SEQ and GSMA 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 will have a massive impact on the performance of the transport network. While 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 dominance of the car is the commuter modal share.

6. Mixed logit model results

The model results for mixed logit models for SEQ and GSMA are presented in Table 6. Account is taken in estimation for observations associated with the same respondents (i.e., the data on each of the 7 days of the week). The overall fit of the models is impressive with a McFadden Pseudo R² of 0.52 and 0.55, respectively for the SEQ and GSMA models. Most of the parameter estimates are significant at a 90% confidence level or better, except for travel time for all modes, except active modes, in the SEQ model which is statistically significant at an 80% confidence level and, since it is one of the main variables of interest, it is included in the models. While we cannot be certain, we hypothesise that the role and influence of travel time and cost has dissipated significantly as a result of the reduced weekly commuting activity with WFH occurring frequently at 2 to 3 days a week for many respondents. Individuals are now far less sensitive to travel times and costs leading to its role being reduced compared to pre-COVID-19.

Two parameters in each model were estimated as random to test and account for preference heterogeneity: travel time for all modes except the active modes, and cost. Different parameter distributions were tested (e.g., normal, lognormal, triangular), and the results show that the time and cost of the SEQ model follow a constrained triangular distribution, where the spread of the travel time is 5% of the mean; and the spread of the cost parameters is equal to the mean. We used 100 Halton intelligent draw, noting that we increased this to 1000 and the results were almost identical. The constraint assumption was varied to investigate the extent of preference heterogeneity around the mean and as is shown, the degree of preference heterogeneity for travel time is best described as slight. In the GSMA model, both parameters follow a constrained normal distribution, with a standard deviation equal to the mean.

We investigated every variable presented in Table 6 for both SEQ and the GSMA as well as many other variables, and have not

11 The GSMA includes Newcastle, Sydney, Central Coast, Illawarra, Nowra-Bomaderry, St Georges Basin- Sanctuary Point, Milton-Ulladulla, and Kangaroo Valley-Southern Highlands.
12 The GSMA includes Newcastle, Sydney, Central Coast, Illawarra, Nowra-Bomaderry, St Georges Basin- Sanctuary Point, Milton-Ulladulla, and Kangaroo Valley-Southern Highlands.
13 SEQ includes Brisbane, Gold Coast, Sunshine Coast, Ipswich and Gympie.
14 This is a relevant model using Wave 3 data of an ongoing study which will be estimating new models as we add additional waves of data over the 2021–22 period.
15 We estimated a series of nested logit models as well as error components models, distinguishing time of day of commuting vs WFH and No-Work. Best (in terms of goodness of fit and inclusion value parameters consistent with generalised extreme value maximisation (i.e., the 0–1 bound on parameter estimates). The best Nested logit models for the GSMA were (i) WFH and No-Work compared to commuting in peak periods (Tods 1 and 3) vs off peak and (ii) WFH and No-Work compared to commuting by car modes (car driver, car passenger, ride share) versus but other models Public transport, walk, bicycle. However, the overall fit was 0.391 and 0.323 respectively, considerably lower than mixed logit. The error components model was not very good with all error component not statistically significant different from unity. For the GSMA we could not found an appropriate nested structure.
16 We ran the same functional forms for the random parameters for both the SEQ and GSMA but did not find statistically significant parameters across both data sets to enable us to adopt the same distributions for preference heterogeneity. In a sense this should not a priori be expected since we are dealing with geographical settings in which the levels of congestion on the roads and crowding on public transport is quite different as is the incidence of WFH.
included those that were not statistically significant and the 95 percent level of better, the exception being travel time in SEQ). The most interesting results relate to the distance of the commuting trip and the biosecurity concern associated with using regular public transport. We see that when the distance of the commuting trip increases, there is a heightened probability of working from home for the SEQ; however, it was not significant for the GSMA (reinforced below by a flat probability of WFH in Fig. 12 and Appendix Table A2). For the SEQ, those who spend more days WFH tend, on average, to have a longer commute (Fig. 12 and Appendix Table A1). As the number of days WFH increases, we see a reduction, on average, in the number of weekly commuting trips, as expected (Fig. 12). As the number of days WFH increases, we see on average what appears to be a U-shaped relationship (for weekdays) with the average number of weekly non-commuting trips, being at its greatest for 2 and 3 days WFH per week and at its lowest when WFH occurs on 4 or 5 days per week (see Fig. 12). This is the first time we have observed this and reported it.

For the GSMA, we investigated this further and found that occupation was a statistically significant surrogate for distance to the regular work office in the GSMA (i.e., if we removed the occupation dummy variables, the commute distance became statistically significant and positive). There is an expected significant industry and occupation influence on the willingness to WFH; where industry grouping is statistically significant in the SEQ and occupation is statistically significant for the GSMA.

A number of dummy variables were included to test for differences in the probability of WFH compared to the modal and No-Work alternatives. For SEQ, we find that the Brisbane CBD (postcodes 4000 and 4006) has a statistically significant and positive effect suggesting that workers in the Brisbane CBD have a higher probability of WFH after controlling for other influences more generally such as industry affiliation, socioeconomic influences (income, age, household size, car ownership), and concerns are bio-security of public transport use. We did not find a statistically significant difference between the Gold Coast, Sunshine Coast and Greater Brisbane area. For the GSMA we see a statistically significant and negative influence of residing in Newcastle and Wollongong compared the Sydney Metropolitan area after controlling for influences such as occupation and other socio-demographics effects.

We also investigated the role that the day of the week plays and found for the SEQ that Monday through to Thursday dummy variables have a positive and statistically significant influence on the probability of WFH compared to Friday and the weekend; however, for the GSMA we find that Monday, Tuesday, Thursday and Friday dummy variables have a negative and statistically significant effect on the probability of WFH compared to Wednesday and weekend days. It is important to identify and control for these day of week effects since it is necessary to establish the extent of peakedness of commuting activity across the week since this has serious implications on the capacity requirements of the road and public transport network. The descriptive data supports a somewhat flat profile throughout the week which is an important result (see Figs. 5 and 6 in Section 3). Finally, we included a series of time of day dummy variables in the utility expressions for all of the modes, finding that for SEQ and the GSMA, a single dummy variable for the morning and afternoon peaks and evening dummy variables, compared to the period between the peaks (set to zero), were positive and statistically significant.

The value of travel time savings for these models is presented in Table 7. The results suggest that the VoT is significantly higher in the GSMA than in the SEQ area. This is in part due, we suggest, to personal incomes being higher (mean and standard deviation) in the GSMA (Table 3) as well as a greater percent of respondents in the professional occupation class; but also that congestion remains higher (even if less than pre-COVID-19) in the GSMA. However, the mean estimate for the GSMA is higher than the recommended guidelines.

### Table 3

Descriptive profile of respondents - mean (standard deviation).

| Variables | SEQ | GSMA |
|-----------|-----|------|
| Age | 38.49 (12.7) | 39.18 (12.2) |
| Average personal annual income (AUD$000) | 81.34 (74.3) | 90.21 (60.4) |
| Number of people in the same household | 2.67 (1.3) | 2.83 (1.3) |
| Number of cars in your household | 1.09 (1.5) | 1.53 (0.9) |
| Number of children in household | 1.61 (0.9) | 1.77 (1.0) |
| Number of modes available | 2.92 (1.4) | 2.92 (1.4) |
| Proportion who used car as driver to commute prior to COVID-19 | 0.619 | 0.510 |
| Distance from home to regular workplace location (kms) | 18.72 (16.7) | 22.28 (29.5) |
| Proportion of sample who are blue collar workers | 0.081 | 0.078 |
| Proportion of workers who have a high level of concern about using PT | 0.542 | 0.575 |
| Occupation professional (1,0) | 0.375 | 0.375 |
| Occupation manager (1,0) | 0.141 | 0.176 |
| Occupation sales (1,0) | 0.080 | 0.072 |
| Occupation clerical and administration (1,0) | 0.259 | 0.236 |
| Occupation community and personal services (1,0) | 0.064 | 0.072 |
| Occupation technology (1,0) | 0.049 | 0.053 |
| Occupation machine operators (1,0) | 0.000 | 0.007 |
| Occupation labourers (1,0) | 0.000 | 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 |
| QLD – Gold Coast residential location (1,0) | 0.215 | – |
| QLD – Sunshine Coast residential location (1,0) | 0.129 | – |
| Work located in CBD (1,0) (SEQ = 4000, 4006 postcodes; GSMA = 2000, 2007, 2009 and 2011 postcodes) | 0.210 | 0.245 |
| Number of respondents | 247 | 409 |
| Number of observations (respondents-day of week) | 1,718 | 2,825 |
in NSW of $17.72/person hour, suggesting that individuals are willing to pay more to save travel times in the presence of a high incidence of WFH, due essentially to reduced commuting activity, and hence less travel expense outlaid. This is the opposite to that recommended for the SEQ which uses a slightly lower mean estimate than NSW. We remain open as to whether the mean estimate of commuting VoT is likely to be higher or lower than pre-COVID-19 as a result of reduced commuting activity. A lower estimate might relate to an hypothesis that individuals who tend to commute more due to the essential nature of their work, tend to have lower incomes and hence represent the population of commuters who generally have a lower mean estimate of VoT. To investigate this, we 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. What this indicates is that there is indeed a 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 an hypothesis that reduced commuting activity means that an individual is willing to pay more to save time simply because they commute less and hence have more travel budget to spend to maximise the utility of commuting. This is a theme worthy of further research, and one we plan to investigate with data from future Waves.

We also calculated, for the GSMA, the reduction in time and money costs from commuting during the period of the Wave 3 survey (Table 8), and found that close to 50% of the pre-COVID-19 time outlays were ‘saved’. On average, each commuter saved $2949 per annum in the SEQ and $3546 in the GSMA, of which $779 and $906 respectively is out of pocket costs. We derived the direct and cross point share elasticities for travel time and fare as summarised in Table 9. These results align quite well with ranges typically reported in the broader literature, even though these travel time and fare elasticities are at the lower end suggesting that there is less sensitivity to travel times given the reduced amount of commuting trips. Note that the access, egress and

17 All the assumptions are presented in Hensher et al. (2021), but unlike that paper where we used Wave 2 data in the current paper we have used Wave 3 data.
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Table 5
Modal availability and Shares in the presence of WFH and No Work.

| Availability  | SEQ %  | GSMA area % |
|----------------|--------|-------------|
| No Work        | 100.0% | 100.0%      |
| WFH            | 66.0%  | 68.9%       |
| Car driver     | 83.0%  | 71.6%       |
| Car passenger  | 42.9%  | 34.5%       |
| Taxi/ride share| 34.4%  | 29.8%       |
| Train          | 32.4%  | 46.9%       |
| Bus            | 48.2%  | 52.3%       |
| Light rail     | 5.7%   | 6.8%        |
| Ferry          | 3.2%   | 2.4%        |
| Walking        | 20.2%  | 25.7%       |
| Bicycle        | 13.4%  | 15.9%       |
| Motorcycle     | 5.3%   | 6.4%        |

Number of respondents

| Choices  | SEQ | GSMA |
|----------|-----|------|
| No Work  | 247 | 409  |
| WFH      |     |      |
| Car driver |    |      |
| Car passenger | |      |
| Taxi/ride share |  |      |
| Train | 2,126 | 3,409 |
| Bus | 6,240 | 10,345 |
| Light rail | 1,577 | 2,615 |
| Ferry | 414 | 689 |
| Walking | 3,126 | 5,301 |
| Bicycle | 7,146 | 11,744 |
| Motorcycle | 1,577 | 2,615 |

Number of respondents-DoW

| SEQ         | 1,718 |
|-------------|-------|
| GSMA        | 2,825 |

wait time for public transport is statistically significant for SEQ but not for the GSMA. The lack of significance for the GSMA, even after assessing each of the three service level attributes separately may be because of both the significantly reduced use of public transport (7.3% of the sample); however, for the SEQ is it also low (at 6.2%) (Table 5), and the mean service levels are also very similar.

The model formulation for the SEQ and GSMA data provides an understanding on the incidence of the probabilities of no work, work from home and commuting. The results are presented in Table 10. This is an important finding which can be used to adjust the pre-COVID-19 commuting modal probabilities used to obtain modal shares. On average we can see that as of September 2020, 6 months into the pandemic, that the mean probability of WFH is 0.196 for SEQ and 0.260 for GSMA. However, if we focus only on WFH versus commuting (assuming the respondent already decided to work), the average probability of WFH is 0.30 for the SEQ and 0.39 for the GSMA. What this suggests is that on any ToD and DoW when the individual works (regardless of location), that if there are, for example, 100 individuals who work, 30 are predicted to WFH in SEQ. When translated into the Days of the Week, subject to variability across the days in WFH, which is relatively flat (see Fig. 5), we predict that the average days working from home per week, including weekends is 2.1; or if we exclude weekends it is 1.5 days per week, resulting in 3.5 days per week of commuting. Given two one-way commuting trips per day, this is equivalent to 7 one-way weekly commuting trips, down from a typical 10 such trips. The equivalent evidence for the GSMA suggest that average days working from home per week, including weekends is 2.73; or if we exclude weekends it is 1.95 days per week, resulting in 3.05 days per week of commuting. Given two one-way commuting trips per day, this is equivalent to 6.1 one-way weekly commuting trips. Even allowing for the pre-COVID-19 incidence of WFH at 4.6% 18, this is a substantial change.

The overall predictive performance of the SEQ and GSMA models is summarised in Table 10. The ability to reproduce the aggregate number of No-Work and WFH periods (ToD by DoW) as well as the quantum of overall commuting activity is impressive. Within the specific models by the four time of day, there are varying degrees of predictive reproduction of actual numbers for each mode. This can be corrected through calibration on known modal shares for each time of day in a real world application where time of day effects need to be accounted for.

In addition, we wanted to set out a mapping between the probability of WFH compared to the probability of commuting and contextual influences. To do this we adjusted the probabilities at a respondent level to remove the probability of no work. The kernel density distributions for the probability of WFH and Commuting, summing to 1.0, at a respondent level and 100% at a sample level are shown in Fig. 13 and Fig. 14 for the SEQ and GSMA models, respectively.

7. Mapping the probability of working from home with socioeconomic and contextual influences

A linear regression model was estimated with the probability of WFH as the dependent variable (considering that the respondent already decided to work that day, i.e., excluding the no work alternative), and several socio-economic and contextual influences as explanatory variables. To ensure that the probability of working from home satisfies the 0–1 bound we imposed a non-linear constraint

18 Source:: Australian Bureau of Statistics, 2016 Census Journey to Work
Table 6
Model results SEQ and GSMA, Wave 3 (September 2020).

| Parameters | Acronym | Alternatives | SEQ Mean (t value) | GSMA Mean (t value) |
|------------|---------|--------------|-------------------|-------------------|
| ASC no work | ASC_NoWork | 1 | – | – |
| ASC work from home | ASC_WFH | 2 | –2.239 (5.94) | – |
| ASC car driver/motorcycle | ASC_CarMoto | 3, 12, 13, 22, 23, 32, 33, 42 | –0.889 (4.30) | –0.203 (1.01) |
| ASC car passenger | ASC_CarP | 4, 13, 24, 34 | –2.086 (9.78) | –1.654 (7.75) |
| ASC taxi/ridesharing | ASC_Taxi | 5, 15, 25, 35 | –4.233 (6.79) | –3.600 (6.69) |
| ASC public transport | ASC_PT | 6–9, 16–19, 26–29, 36–39 | –1.761 (7.27) | –1.410 (7.86) |
| ASC active modes | ASC_Act | 10, 11, 20, 31, 40, 41 | –0.426 (1.67) | –0.877 (3.44) |
| ASC ToD 1 and 3 | ASC_T13 | 3–12, 23–32 | 0.513 (5.23) | 0.391 (4.94) |
| ASC ToD 2 | ASC_T2 | 13–22 | – | – |
| ASC ToD 4 | ASC_T4 | 33–42 | 4.233 (6.79) | 3.600 (6.69) |
| No Work - Age | Age_NW | 1 | 0.026 (7.27) | 0.074 (10.36) |
| No Work - Male (1,0) | Male_NW | 1 | – | –0.326 (3.55) |
| WFH - Distance from home to work | DistWFH_WFH | 2 | 0.011 (2.50) | – |
| WFH - Age | Age_WFH | 2 | 0.018 (2.96) | – |
| WFH - Number of people in household | HPers_WFH | 2 | 0.105 (1.88) | – |
| WFH - Income | Inc_WFH | 2 | 0.006 (3.80) | – |
| WFH - Proportion of workers who have a high level of concern about using PT | ConcPT_WFH | 2 | 0.482 (3.27) | 0.477 (4.39) |
| WFH - Professional (industry category) (1,0) | Prof_WFH | 2 | 0.957 (5.70) | – |
| WFH - Industry (industry category) (1,0) | Ind_WFH | 2 | 0.494 (2.46) | – |
| WFH - Occupation professional (1,0) | OcProf_WFH | 2 | – | 5.184 (12.50) |
| WFH - Occupation manager (1,0) | OcMng_WFH | 2 | – | 5.235 (12.25) |
| WFH - Occupation sales (1,0) | OcSale_WFH | 2 | – | 4.507 (10.03) |
| WFH - Occupation clerical and administration (1,0) | OcAdm_WFH | 2 | – | 5.071 (12.04) |
| WFH - Occupation community and personal services (1,0) | OcCom_WFH | 2 | – | 3.849 (7.47) |
| WFH - Occupation blue collar worker (1,0) | OcBlcl_WFH | 2 | – | 5.058 (11.34) |
| WFH - Monday dummy variable (1,0) | DMon_WFH | 2 | 1.366 (6.49) | –1.325 (8.17) |
| WFH - Tuesday dummy variable (1,0) | DTue_WFH | 2 | 1.135 (5.34) | –1.333 (8.18) |
| WFH - Wednesday dummy variable (1,0) | DWed_WFH | 2 | 1.126 (5.27) | – |
| WFH - Thursday dummy variable (1,0) | DThu_WFH | 2 | 1.316 (6.24) | –1.044 (6.44) |
| WFH - Friday dummy variable (1,0) | DFri_WFH | 2 | – | –0.975 (6.07) |
| WFH NSW - Wollongong residential location (1,0) | Woll_WFH | 2 | – | –0.571 (2.76) |
| WFH NSW - Newcastle residential location (1,0) | Newc_WFH | 2 | – | –0.855 (4.24) |
| WFH QLD - work located in CBD (1,0) | CBD_WFH | 2 | 0.309 (1.98) | – |
| Car driver - Income | Inc.CarD | 3, 13, 23, 33 | 0.005 (3.16) | 0.002 (1.97) |
| Car driver - Number of cars in household | NCAR.CarD | 3, 13, 23, 33 | – | 0.339 (3.33) |
| Car driver - Number of cars per person in household | NCAR.CarD | 3, 13, 23, 33 | – | 0.149 (3.23) |
| Travel time all modes except active - mean | TT_CarPT | 3–9, 12–19, 22–29, 32–39, 42 | –0.003 (1.35) | –0.029 (4.98) |
| - standard deviation | | | 0.00015 (1.35) | 0.029 (4.98) |
| Travel time walking | TT_Walk | 10, 20, 30, 40 | –0.028 (4.93) | –0.029 (4.70) |
| Travel time bicycle | TT_Bike | 11, 21, 31, 41 | –0.029 (3.02) | –0.043 (3.30) |
| Cost all modes except car pax and active - mean | Cost_CarPT | 3, 5–9, 12, 13, 15–19, 22, 23, 25–29, 32, 33, 35–39, 42 | –0.019 (2.52) | –0.068 (4.34) |
(continued on next page)
so as to satisfy this condition. The results of this regression are presented in Table 11. The overall explanatory power for the disaggregated data is 0.86 and 0.82 respectively for SEQ and the GSMA, which is an impressive capturing of sources of systematic variation in the probability of WFH (or conversely of commuting). Such a mapping model is very useful for identifying adjustments in the probability of commuting as a result of the incidence of WFH, and within the setting of strategic transport models, the segments based of a rich array of socioeconomic and contextual profiles can be used to create a distribution of WFH incidence that is typically useful at an origin–destination level. For example, if the transport analyst responsible for a strategic transport model system obtains the mean values for each of the relevant explanatory variables in Table 11 for a given origin–destination pair, they can then obtain an estimate of the probability of WFH, and hence adjust the incidence of commuting on particular days of the week and weekend. Friday

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**Table 6 (continued)**

| Parameters | Acronym | Alternatives | SEQ Mean (t value) | GSMA Mean (t value) |
|-----------|---------|--------------|-------------------|--------------------|
| - standard deviation | | | 0.019 (2.52) | 0.068 (4.34) |
| Access + egress + waiting time taxi/PT modes | TTAEW | 5–9, 15–19, 25–29, 35–39 | –0.012 (2.44) | – |
| Number of parameters estimated | | | 30 | 30 |
| Sample size | | | 1,718 | 2,825 |
| Log Likelihood at convergence | | | 3,097.11 | 4,775.84 |
| Log likelihood at zero | | | 6,421.32 | 10,558.92 |
| McFadden Pseudo R squared | | | 0.52 | 0.55 |
| AIC/n | | | 3.64 | 3.40 |

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**Table 7**

Value of travel time SEQ and GSMA models (AUD$).

| Mean (AUD$) | 95% Confidence interval |
|-------------|-------------------------|
| SEQ | 15.64 | 6.23 | 45.16 |
| GSMA | 26.02 | 9.17 | 42.85 |

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**Table 8**

The change in annualised commuting time and out-of-pocket costs

| This DSS includes those who work before and after Covid who work at least one day from home |
| SEQ | Other QLD | GSMA | Other NSW |
|---|---|---|---|
| 1) How many days they worked per week before COVID? - days | 4.69 | 4.88 | 4.64 | 4.64 |
| 2) How many days they WFH before COVID? - days | 1.31 | 1.81 | 1.16 | 2.15 |
| 3) How many days they worked last week? - days | 4.33 | 4.23 | 4.4 | 3.79 |
| 4) How many days they WFH last week? - days | 3.35 | 2.9 | 3.65 | 2.94 |
| 5) How many minutes it takes to get to work via their main mode? (one-way) - minutes | 31.9 | 24.8 | 34.1 | 29.6 |

Outputs

| Total commuting time spent before COVID per week (both ways in mins) | 216 | 152 | 237 | 147 |
| Total commuting time spent last week (both ways in mins) | 63 | 66 | 51 | 50 |

**Time and Cost Saving due to COVID/WFH**

| Weekly time saving in commuting time (mins) | 153 | 86 | 186 | 97 |
| Annual time saving in commuting time (hours) | 122.5 | 69.0 | 148.9 | 77.7 |
| Total annual cost saving on travel time ($) | $2,171 | $1,233 | $2,639 | $1,376 |
| Other annual costs saving (e.g., car fuel, fare, and toll etc) | $779 | $439 | $906 | $473 |
| Total annual cost saving ($) | $2,949 | $1,662 | $3,546 | $1,849 |
Table 9
Illustrative Direct and cross share elasticities for travel time (all modes) and fares (public transport and ride share), probability weighted by the probability of a mode being chosen.

9a GSMA Travel Time and Fare for Morning Peak

| Travel Time | No Work | WFH | Car Driver | Car Pax | Ride Share | Train |
|-------------|---------|-----|------------|---------|------------|-------|
| Car Driver  | 0.0120  | 0.0117 | –0.1690 | 0.0123 | 0.0097 | 0.0090 |
| Car Pax     | 0.0011  | 0.0011 | 0.0011 | –0.1829 | 0.0009 | 0.0010 |
| Ride Share  | 0.0001  | 0.0001 | 0.0001 | 0.0001 | 0.1659 | 0.0000 |
| Train       | 0.0028  | 0.0030 | 0.0015 | 0.0018 | 0.0025 | –0.2230 |
| Bus         | 0.0021  | 0.0019 | 0.0015 | 0.0013 | 0.0026 | 0.0020 |
| LRT         | 0.0003  | 0.0004 | 0.0001 | 0.0002 | 0.0005 | 0.0000 |
| Ferry       | 0.0001  | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0000 |
| Walk        | 0.0049  | 0.0024 | 0.0035 | 0.0042 | 0.0051 | 0.0030 |

| Travel Time | Bus | LRT | Ferry | Walk | Bike | Moto |
|-------------|-----|-----|-------|------|------|------|
| Car Driver  | 0.0087 | 0.0051 | 0.0092 | 0.0039 | 0.0035 | 0.0097 |
| Car Pax     | 0.0008 | 0.0007 | 0.0012 | 0.0005 | 0.0005 | 0.0011 |
| Ride Share  | 0.0002 | 0.0002 | 0.0003 | 0.0001 | 0.0001 | 0.0002 |
| Train       | 0.0031 | 0.0038 | 0.0030 | 0.0009 | 0.0006 | 0.0012 |
| Bus         | 0.2827 | 0.0023 | 0.0028 | 0.0008 | 0.0010 | 0.0018 |
| LRT         | 0.0005 | –0.2040 | 0.0032 | 0.0001 | 0.0002 | 0.0006 |
| Ferry       | 0.0001 | 0.0011 | –0.2487 | 0.0000 | 0.0001 | 0.0005 |
| Walk        | 0.0051 | 0.0039 | 0.0022 | –0.7369 | 0.0103 | 0.0029 |

| Travel Time | No Work | WFH | Car Driver | Car Pax | Ride Share | Train |
|-------------|---------|-----|------------|---------|------------|-------|
| Train       | 0.0003  | 0.0003 | 0.0001 | 0.0002 | 0.0002 | –0.0210 |
| Bus         | 0.0001  | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0000 |
| LRT         | 0.0000  | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Ferry       | 0.0000  | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Walk        | 0.0000  | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

9b SEQ Travel Time and Fare for Morning Peak

| Travel Time | No Work | WFH | Car Driver | Car Pax | Ride Share | Train |
|-------------|---------|-----|------------|---------|------------|-------|
| Car Driver  | 0.0067  | 0.0061 | –0.0698 | 0.0070 | 0.0051 | 0.0050 |
| Car Pax     | 0.0010  | 0.0005 | 0.0008 | –0.0782 | 0.0006 | 0.0000 |
| Ride Share  | 0.0000  | 0.0000 | 0.0000 | 0.0000 | 0.0002 | 0.0000 |
| Train       | 0.0007  | 0.0006 | 0.0004 | 0.0002 | 0.0004 | –0.0990 |
| Bus         | 0.0011  | 0.0009 | 0.0006 | 0.0008 | 0.0014 | 0.0020 |
| LRT         | 0.0001  | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0000 |
| Ferry       | 0.0000  | 0.0000 | 0.0000 | 0.0000 | 0.0001 | 0.0000 |
| Walk        | 0.0070  | 0.0043 | 0.0044 | 0.0075 | 0.0146 | 0.0020 |

| Travel Time | Bus | LRT | Ferry | Walk | Bike | Moto |
|-------------|-----|-----|-------|------|------|------|
| Car Driver  | 0.0036 | 0.0074 | 0.0026 | 0.0016 | 0.0028 | 0.0070 |
| Car Pax     | 0.0005 | 0.0006 | 0.0004 | 0.0004 | 0.0001 | 0.0005 |
| Ride Share  | 0.0000 | 0.0000 | 0.0001 | 0.0000 | 0.0000 | 0.0000 |
| Train       | 0.0012 | 0.0005 | 0.0014 | 0.0001 | 0.0003 | 0.0005 |
| Bus         | 0.0920 | 0.0008 | 0.0002 | 0.0006 | 0.0009 | 0.0010 |
| LRT         | 0.0001 | –0.0876 | 0.0005 | 0.0000 | 0.0000 | 0.0000 |
| Ferry       | 0.0001 | 0.0002 | –0.0629 | 0.0001 | 0.0001 | 0.0000 |
| Walk        | 0.0109 | 0.0138 | 0.0134 | –0.8755 | 0.0201 | 0.0029 |

| Travel Time | No Work | WFH | Car Driver | Car Pax | Ride Share | Train |
|-------------|---------|-----|------------|---------|------------|-------|
| Train       | 0.0005  | 0.0005 | 0.0004 | 0.0002 | 0.0003 | –0.0800 |
| Bus         | 0.0007  | 0.0005 | 0.0004 | 0.0005 | 0.0009 | 0.0010 |
| LRT         | 0.0001  | 0.0000 | 0.0001 | 0.0001 | 0.0001 | 0.0000 |
| Ferry       | 0.0000  | 0.0000 | 0.0000 | 0.0000 | 0.0001 | 0.0000 |

| Travel Time | Bus | LRT | Ferry | Walk | Bike | Moto |
|-------------|-----|-----|-------|------|------|------|
| Train       | 0.0008 | 0.0004 | 0.0007 | 0.0001 | 0.0001 | 0.0000 |
| Bus         | 0.0574 | 0.0007 | 0.0009 | 0.0006 | 0.0007 | 0.0007 |
| LRT         | 0.0001 | –0.0551 | 0.0003 | 0.0001 | 0.0001 | 0.0000 |
| Ferry       | 0.0001 | 0.0002 | –0.0448 | 0.0001 | 0.0001 | 0.0000 |
Table 10
Predicted versus actual choice numbers for WFH, no work and commute in SEQ and GSMA models.

| SEQ  | NOWORK | WFH | Commute | CARD | CARP | RSH | TRAIN | BUS | LRT | FERRY | WALK | BIKE | MotorB | PT | Total |
|------|--------|-----|---------|------|------|-----|-------|-----|-----|-------|------|------|--------|----|-------|
| Actual | 588   | 337 | 793     | 521  | 59   | 4   | 35    | 62  | 7   | 4     | 45   | 42   | 17     | 108 | 2514  |
| Predicted | 608   | 337 | 773     | 528  | 59   | 3   | 37    | 62  | 6   | 1     | 54   | 13   | 0      | 106 | 2491  |
| GSMA | NOWORK | WFH | Commute | CARD | CARP | RSH | TRAIN | BUS | LRT | FERRY | WALK | BIKE | MotorB | PT | Total |
| Actual | 952   | 725 | 1148    | 734  | 59   | 10  | 90    | 94  | 13  | 4     | 57   | 59   | 28     | 201 | 3793  |
| Predicted | 987   | 735 | 1103    | 749  | 61   | 7   | 120   | 67  | 11  | 2     | 54   | 16   | 16     | 200 | 3928  |
was not statistically significant for SEQ and Wednesday for the GSMA as was a separate dummy variable for the weekend; hence these are combined with the weekend where the dummy variable is set to zero as the comparator with the estimated parameters for the other days of the week.

To give an example of how the probability of WFH varies by the levels of statistically significant influences, we present the findings for a few socioeconomics and locational influences for the SEQ and GSMA, one at a time, in Fig. 15 and Fig. 16, respectively. Analysts using this mapping device in real applications should use the mean values for each explanatory variable for the spatial context if interest, as discussed above. The results show that as distance from home to work increases between 1 and 40 km, the probability of WFH increases, between 0.38 and 0.510 in the SEQ model, and between 0.28 and 0.40 in the GSMA model. As the personal income in the SEQ area increases, the probability of work from home increases from 0.40 for respondents with an income below $10,000p.a., to 0.60 for respondents with an income of $400,000p.a. or more. The industry categories in the SEQ model have a significant influence over the probability to work from home, where respondents that work in professional industry categories have a WFH probability of 0.55, and respondents that work in retail have a WFH probability of 0.32. In the GSMA model, the occupations of respondents are found to have a significant influence on the WFH probability, where the highest WFH probability is for professional workers (0.41) and the lowest for community and personal service workers (0.14).

8. Conclusions

With working from home likely to remain to some extent after COVID-19 has dissipated in the presence or otherwise of a vaccine, it becomes imperative to find a way to integrate the probability of working from home into current transport model systems, be they at
Table 11
WFH probability mapping model results (linear regression with 0–1 constraint) Note: confidence intervals are available on request.

| Parameters                          | SEQ Mean (t value)       | GSMA Mean (t value)       |
|------------------------------------|--------------------------|---------------------------|
| Constant                           | −0.022 (1.52)            | 1.015 (29.9)              |
| Age                                | 0.004 (16.5)             | −                        |
| Income                             | 0.001 (9.02)             | −                        |
| Distance from home to work         | 0.004 (25.4)             | 0.002 (7.1)              |
| Number of people in household      | 0.026 (14.4)             | −                        |
| Number of cars per person in household | −0.018 (10.7)       | −0.019 (5.97)            |
| Children in primary school (1,0)   | −                       | 0.022 (4.41)             |
| Children in secondary school (1,0) | −0.019(3.03)            | −0.029 (3.11)            |
| Children in tertiary school (1,0)  | −0.045 (5.84)            | −                        |
| Number of modes available          | −0.036 (21.4)            | −0.045 (33.8)            |
| Prior to Covid-19, main mode of transport car driver | −0.066 (9.46) | −0.125 (21.9) |
| High level of concern number of people in PT | 0.082 (14.8) | 0.078 (17.2) |
| Professional (industry category) (1,0) | 0.221 (30.1)          | −                        |
| Industry (industry category) (1,0) | 0.096 (12.8)            | −                        |
| Services (industry category) (1,0) | 0.045 (5.34)            | −                        |
| Occupation professional (1,0)      | −0.033 (5.45)            | 0.421 (13.6)             |
| Occupation manager (1,0)           | −                       | 0.413 (13.1)             |
| Occupation sales (1,0)             | −                       | 0.323 (10.0)             |
| Occupation clerical and administration (1,0) | −0.042 (6.06) | 0.406 (13.1) |
| Occupation community and personal services (1,0) | −0.031 (2.88) | 0.157 (4.87) |
| Occupation labourer (1,0)          | −                       | −0.086 (5.22)            |
| Occupation blue collar worker (1,0) | −                       | 0.391 (12.4)             |
| Work located in GSMA CBD (1,0)     | −                       | 0.069 (12.9)             |
| Work located in SEQ CBD (1,0)      | 0.137 (15.5)             | −                        |
| GSMA Newcastle location (1,0)      | −                       | −0.190 (26.2)            |
| GSMA Illawarra location (1,0)      | −                       | −0.118 (13.5)            |
| GSMA Central Coast location (1,0)  | −                       | −0.026 (2.55)            |
| SEQ Gold Coast location (1,0)      | −0.033 (5.78)            | −                        |
| SEQ Sunshine Coast location (1,0)  | −0.038 (5.25)            | −                        |
| Monday (1,0)                       | 0.274 (38.1)             | −0.243 (37.7)            |
| Tuesday (1,00)                     | 0.225 (31.0)             | −0.245 (38.00)           |
| Wednesday (1,0)                    | 0.224 (30.9)             | −                        |
| Thursday (1,0)                     | 0.263 (36.4)             | −0.194 (29.2)            |
| Friday (1,0)                       | −                       | −0.182 (27.3)            |
| Number of parameters estimated     | 24                      | 23                       |
| Sample size                        | 1,133                    | 1,943                    |
| Adjusted R squared                 | 0.86                     | 0.82                     |

1 The sample size for the WFH probability models is different than the previous models, because it only includes respondents that could WFH, which was available for 66–69% of respondents, presented in Table 5.

Table A1
The relationship between # days WFH and weekly commuting and non-commuting trip activity for the SEQ (linked to Fig. 13)

| #WFH days | Ave commute distance | Ave #one way weekly commute trips | Ave #one-way weekly non-commute trips |
|-----------|----------------------|----------------------------------|--------------------------------------|
| 0         | 15.63                | 7.42                             | 11.71                                 |
| 1         | 15.4                 | 6.15                             | 12.05                                 |
| 2         | 20.84                | 5                                | 14.47                                 |
| 3         | 24.64                | 2.73                             | 14.09                                 |
| 4         | 10.62                | 2                                | 9.25                                  |
| 5         | 24.58                | 1.18                             | 7.89                                  |
| 6         | 36.67                | 1.33                             | 12                                   |
| 7         |                      |                                  |                                       |

Table A2
The relationship between # days WFH and weekly commuting and non-commuting trip activity for the GSMA (linked to Fig. 14)

| #WFH days | Ave commute distance | Ave #one way weekly commute trips | Ave #one-way weekly non-commute trips |
|-----------|----------------------|----------------------------------|--------------------------------------|
| 0         | 14.33                | 7.33                             | 10.44                                 |
| 1         | 22.49                | 7.25                             | 12.29                                 |
| 2         | 24.28                | 5.13                             | 13.7                                  |
| 3         | 24.17                | 3.59                             | 11.48                                 |
| 4         | 20.64                | 2.79                             | 15.89                                 |
| 5         | 24.12                | 2.4                              | 11.43                                 |
| 6         | 18.71                | 0.86                             | 6                                     |
| 7         | 27.83                | 0.83                             | 7.6                                   |
Fig. 15. WFH probability changes by location/socioeconomic changes in SEQ model.
the metropolitan area level or at other geographical jurisdictions\textsuperscript{19}. Although the focus in this paper is on commuter mode choice and how it is expected to be impacted by the incidence of working from home, we have also developed and estimated Poisson regression models\textsuperscript{20} to identify the systematic sources of influence on the number of one-way weekly trips by each mode and trip purpose. We wanted to establish the extent to which working from home changes the amount of such weekly travel activity and we were able to show that for most trip purposes that there was a change, often an increase, in the quantum of non-commuting trips\textsuperscript{21}.

Together with the commuter mode choice model, transport analysts and planners now have a suggested way to revise the current set of mode choice and trip generation models to account for the probability of working from home by socioeconomic and geographical segments. We have considered a number of ways of building the new models into existing strategic transport models and while it is possible to replace existing models with appropriate calibration, it is also feasible and indeed attractive for practitioners who have invested heavily in integrated transport and land use model systems to append these new models as a mechanism to adjust the probabilities (including logsums) of commuting by various modes for specific segments to account for working from home. At a very high aggregate level, the adjustments are likely to be in the vicinity of 0.3 to 0.4 (Table 10) if the evidence from September 2020 is maintained going forward. This adjustment can be done either prior to forecasting or after application. There is one caveat to this approach; namely that we assume that all parameters estimated prior to COVID-19 are appropriate for the post-COVID-19 setting and if not, this will require re-estimation. The particular parameters at risk, as a minimum, are crowding on public transport, the mix of congested and free flow time for a particular trip and reliability of travel time (i.e., travel time variability) for repeated trips on the road network. We will be re-assessing the changes in such attributes in a series of surveys in 2021 (Waves 4 to 7) to understand the stability or otherwise of the parameter evidence used in this paper, from Wave 3.

In ongoing research, in addition to re-estimating the models presented in this paper to look for signs of settling down of the behavioural responses post-COVID-19, we will be calibrating the models into a strategic model system to assess the likely traffic predictions in the presence and absence of the anticipated levels of working from home post-COVID-19. With three waves of data and an additional one recently collected in June 2021, we can start thinking about a longitudinal assessment. There are caveats however. Wave 1 is a standalone convenience sample, with Wave 2 the beginning of systematic sampling throughout Australia, but with greater sample sizes in NSW and Queensland given the sources of funding. Some of the participants in Wave 2 were in Wave 3 but a relatively small number, with Wave 3 having a high proportion of first time respondents. This means that although the panel nature of the data is

\textsuperscript{19} We have developed similar models for regional towns in Queensland and New South Wales.

\textsuperscript{20} Given that the dependent variable is count data and hence not continuous, regression-based methods are not appropriate. Earlier models were developed for Wave 2 (Hensher et al. 2020).

\textsuperscript{21} This research will be reported in a subsequent paper.
limited, we are still able to consider a longitudinal assessment through a formal modelling framework

Contributions

David Hensher undertook all model estimation and interpretation and drafted the initial versions of the paper as well as contributed to final editing; Camila Balbontin prepared and cleaned the data for modelling as well as contributed to preparation of the paper and final editing; Matthew Beck designed the survey instrument and prepared the descriptive profile as well as writing various sections and editing the final version; Edward Wei designed the decision support system used to create the graphs for various socioeconomic and context variables associated with the probability of working from home.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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