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Accounting for the spatial incidence of working from home in an integrated transport and land model system

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ABSTRACT: The COVID-19 pandemic has resulted in a seismic shift in the way in which work is conducted. Remote working or working from home is becoming a centrepiece of the next normal with strong support from both employers and employees. With reduced commuting activity associated with an expected 1 to 2 days working from home for many occupations and industries, associated with releasing commuting time to spend on other activities including changed levels and patterns on non-commuting travel, it is necessary, indeed essential, to allow for the incidence of working from home in integrated strategic transport and location model systems. In this paper we show the extent of changes in travel behaviour and the performance of the transport network before and after allowing for working from home which is more impactful than any new infrastructure project. The differences are significant and suggest that even within the existing modelling frameworks used pre-COVID-19, we need to make adjustments in the modal activity overall and by location. Using the MetroScan platform in the Greater Sydney Metropolitan area, we present a number of outputs to illustrate the significant impacts of working from home such as modal activity (total and shares), emissions, government revenues, and generalised cost of travel.

KEY WORDS: ***Working from home, impacts on travel demand and networks, integrated transport and land use strategic model system, emissions, MetroScan.***

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1. Introduction

The extreme event, COVID-19, has resulted in a number of unintended consequences of which the extent and support for working from home (WFH) or remote working has been both surprising and generally welcomed by employees and employers. Since the beginning of the pandemic in March 2020, there has been a significant amount of WFH in lockdown and non-lockdown states in many countries. While we have seen a proliferation of descriptive assessments of the extent of WFH and the levels of support including productivity benefits, flexibility in work arrangements and general lifestyle benefits and costs (e.g., Beck and Hensher 2021a, 2021b, Barrero et al. 2020, Hill et al. 2010), there is a dearth of research that formally analyses, during the current pandemic period, the spatial relationship between WFH and the performance of the transport network, including trip making levels, travel times and emissions. Kim et al. (2015) is an example of such a modelling effort pre-COVID-19 when WFH (or telecommuting) was significantly less. Moeckel (2017) is the best example of an effort using an integrated transport and land use framework to account for working from home pre-pandemic, but the focus is only on the impact that WFH has on travel times within the transport model MATSim (www.matsim.org) as integrated with the land use model SILO (www.silo.zone).

To achieve an understanding of spatial variations and impacts of WFH, we use MetroScan, developed by the authors (Hensher et al. 2020), as a strategic-level transport and land use planning application system which allows for mapping of passenger and freight activity, as well as an endogenous treatment of the location of households and firms. We modify Metroscan to include the probability of WFH as obtained from an ongoing longitudinal research project that commenced in March 2020 and will continue through to 2023 (see Hensher et al. 2021). The longitudinal perspective is essential to gain an understanding of the changing state of WFH, and to be able to gain confidence in establishing a level of WFH that appears to be reliable in future investigations of its impact on travel behaviour and network performance.

The main model change involves using a mapping equation developed by Hensher et al. (2022) for the Greater Sydney Metropolitan Area (GSMA), that enables us to obtain an estimate of the probability of WFH (compared to commuting from a commuting mode choice and time of day model) at an origin-destination level, as determined by socioeconomic and other drivers which have been parametrised from the latest wave of longitudinal data (June 2021), and used with aggregate data describing each origin and destination. We also incorporate changes in the amount of non-commuting trip activity consequent on WFH through elasticity estimates obtained from a Poisson regression model of one way weekly trips for a number of trip purposes. In addition, we account for the influence that changing levels of commuting and non-commuting have on network travel times, supported by trip-purpose specific equations that relates pre-COVID-19 travel times to travel times with WFH during COVID-19. These equation are embedded in the traffic assignment algorithm to obtain revised travel times on the road network.

The paper is structured as follows. We begin with a summary overview of Metroscan as a way of setting out the framework within which we embed working from home. This is followed by the WFH modelling results used to obtain a mapping between location-specific influences on WFH and the probability of WFH. We then present the results associated with a base with and without WFH and the project application with and without accounting for WFH. A case study is then presented for an extension to a tolled motorway in Sydney, followed by the empirical results to show the influence on WFH compared to a new project treatment. We choose a number of key behavioural outputs to account for the impact of WFH such as levels of travel activity, modal shares, emissions and energy, revenues, modal generalised cost, and accidents. The paper concludes with comments on the future role of WFH in transport planning activity where we consider both 'predict and provide' and 'vision and validate'.

2. The MetroScan Structure

One of the most important features of comprehensive land use and transport planning is an ability to identify candidate projects and policies that add value to the sustainable performance of transport networks and to the economy as a whole. There is a case to be made for having a capability to undertake, in a timely manner, a scan of a large number of potentially worthy projects and policies that can offer an understanding as well as forecasts of passenger and freight demand responses to specific initiatives. Such a framework would then be meaningful in the sense of offering outputs that are similar to those that are the focus of assessments that are typically spread over many months, if not years, on very few projects, which may exclude those which have the greatest merit. MetroScan, a strategic-level transport and land use planning application system allows for mapping of passenger and freight activity, as well as an endogenous treatment of the location of households and firms. In short, MetroScan is all-in-one assessment and scanning system enabling us to conduct quick predictions of the demand characteristics for cars, public transport, freight activities, and many other travel demand characteristics associated with a base and a project application.

Figure 1 shows how the macro generator works by taking inputs from existing transport models, such as the road and public transport network, and any OD matrices for the starting year to be used as a base, then uses the network travel times and distances by time of day. Characteristics of households, such as dwelling, household types, or car ownership, in synthetic data, carry sociodemographic and behavioural elements into the system. The scheme also uses some defaults for values and distributions to fill in gaps when input data or models do not support such information (e.g., population growth rate or inflation rate). One of the central features of the macro generator is the adoption of macrozones. These macrozones can be predefined using a standard zone definition (e.g., from the Australian Bureau of Statistics), but can also be manually defined in the system. The macro generator can aggregate any OD skims to the macrozone layer. If executed outside the system, this would be a difficult task that can require months to correct. MetroScan has this process automated so changes to any OD skim matrices can be contemplated on the macrozone level when a proposed initiative is being processed. To provide further background, the macro generator applies a data manager to manage imported networks from different origins, such as TRANSCAD, VISUM, EMME, CUBE, and other systems. While preserving the accuracy for fast scanning, the macro generator largely reduces many detailed zones to a manageable number of macrozones, including the ones made by users. By doing so, initiatives under investigation can be assessed very fast in order to generate forecasting results from travel demand and economic impact. A trade-off exists between computation time and accuracy due to the detailed level of the macrozone. For example, in Sydney, there are over 3,000 detailed zones in the transport network. In practice, we would apply 80 macrozones, which could satisfy both accuracies of forecasting and efficiency of the computation process. In reality, the forecasting results for major macro zones would also provide more meaningful and actionable insights for policymakers. Many strategic initiatives also start with higher levels of macrozones and request scanning results at the same level from travel demand to economic impact factors.

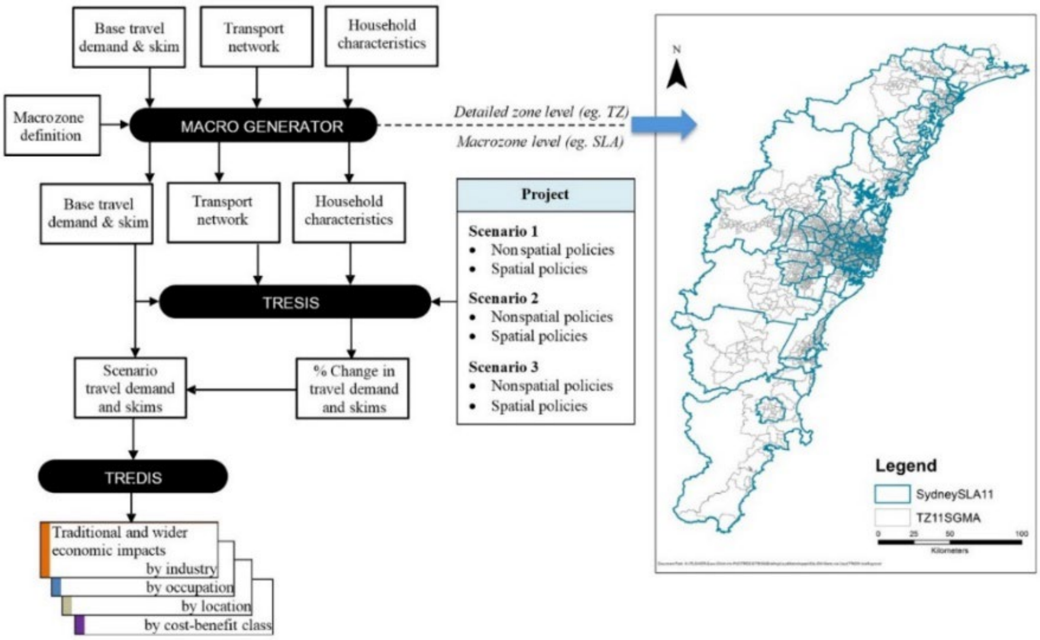


Figure 1. MetroScan framework.

MetroScan was designed to apply synthetic (or proto-typical) households as units to gain numerous responses to alterations in the system driven by both broad and in-depth policy measures. MetroScan applies a large number of choice models on both the macro and micro level, including behavioural aspects, providing more behavioural realistic market responses robust in contrast to traditional model systems (see Figure 2). This enables us to use Metroscan as both a vision and validate system as well as predict and provide system (Jones 2016). MetroScan processes and delivers results for different modes, travel purposes, and time-of-day choices for medium to long-term decisions up to 20 to 35 years (i.e., currently forecasting up to 2056). It also accounts for long-term decisions or choices on vehicle types, fleet size, vehicle technology, residential and work locations, job and firm growth areas, dwelling types, and many others. Besides forecasting commuting, non-commuting trips, such as personal business and social purposes, and business trips; light commercial vehicle and freight commodity models support business activity responses by location, volumes, and trips at macrozone levels. Further details are given in Hensher et al. (2020).

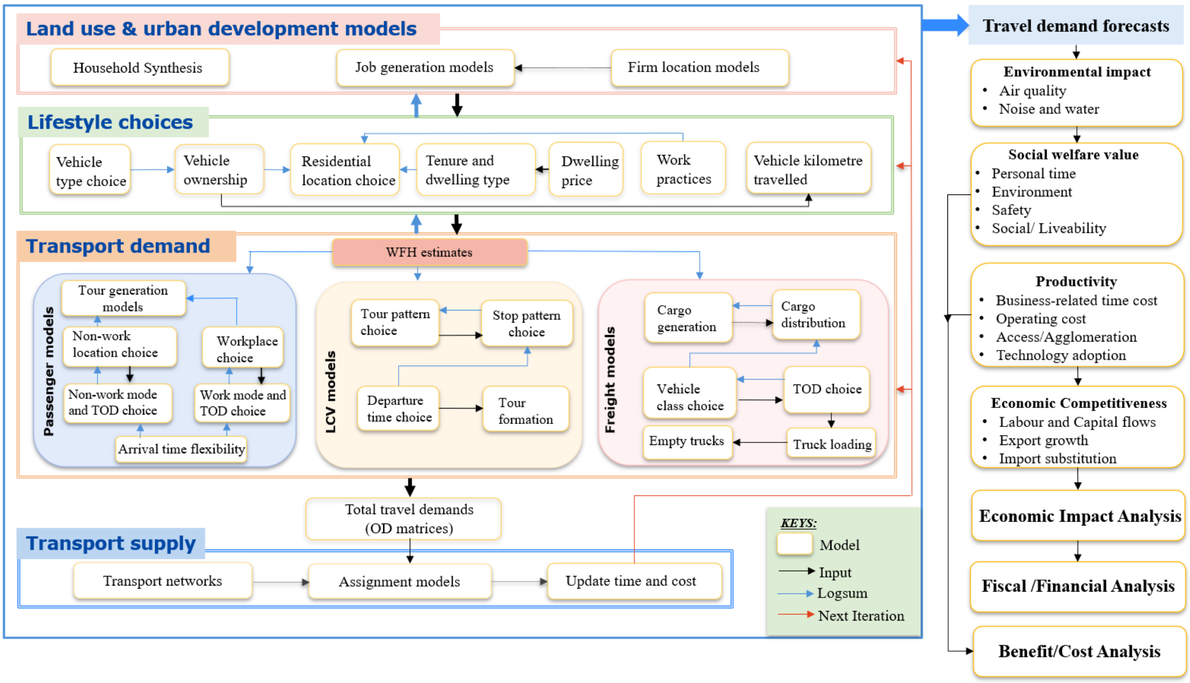


Figure 2. The demand-side behavioural model system for passenger, light commercial, and freight travel activity. Source: Hensher et al. (2020).

3. Identifying the Spatial Incidence of Working from Home and building it into MetroScan

The evidence on WFH is obtained from a separate model system developed as part of an ongoing research project on the implications of WFH on travel and location behaviour (see Beck and Hensher 2021, 2021a). The study area for this analysis was defined as the GSMA, stretching from Newcastle to Wollongong (Figure 3), with a wide range of socio-economic and traffic data being assembled for this area.

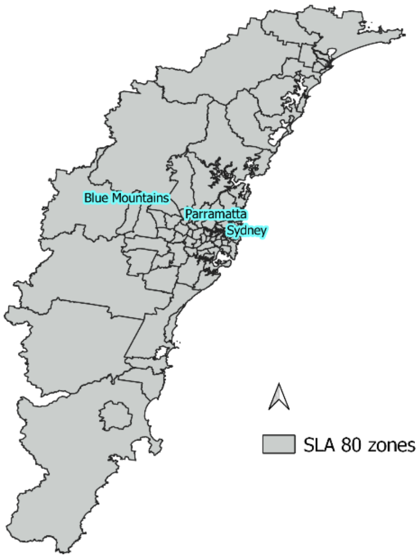


Figure 3: Sydney zones in MetroScan

Two models are used as the baseline for obtaining predictions of the probability of WFH on any day and the key influences of the obtained levels. We have presented the model structure in Hensher et al. (2022) using the data from the September 2020 time period (called Wave 3) in our ongoing longitudinal data collection in Australia. The commuter mode and time of day choice model with embedded WFH choice used in this paper is newly estimated using the June 2021 data (called Wave 4) given in Table 1 based on the structure in the top and bottom panels of Figure 4, and we refer readers to Hensher et al. (2022) for fuller details of the methods and interpretation of model results. In summary, we first estimate a commuter mode choice mixed logit model in which the choices are between no work, WFH and up to seven commuter modes for 7 days of the week and 4 times of day (Figure 4) on the sample of commuters, using equations 1- 5 as the utility expressions associated with each alternative. The implied value of in-vehicle travel time is \$22.18/person hour. The estimated model enables us to obtain a prediction of the probability of WFH, and separating out the probability of no work, we obtain the probability of WFH compared to commuting at a particular time of day and day of week. This probability is then used in a mapping equation to identify sources of influence on the probability of WFH, given in Table 2. Descriptive data associated with both models is given in Appendix A.

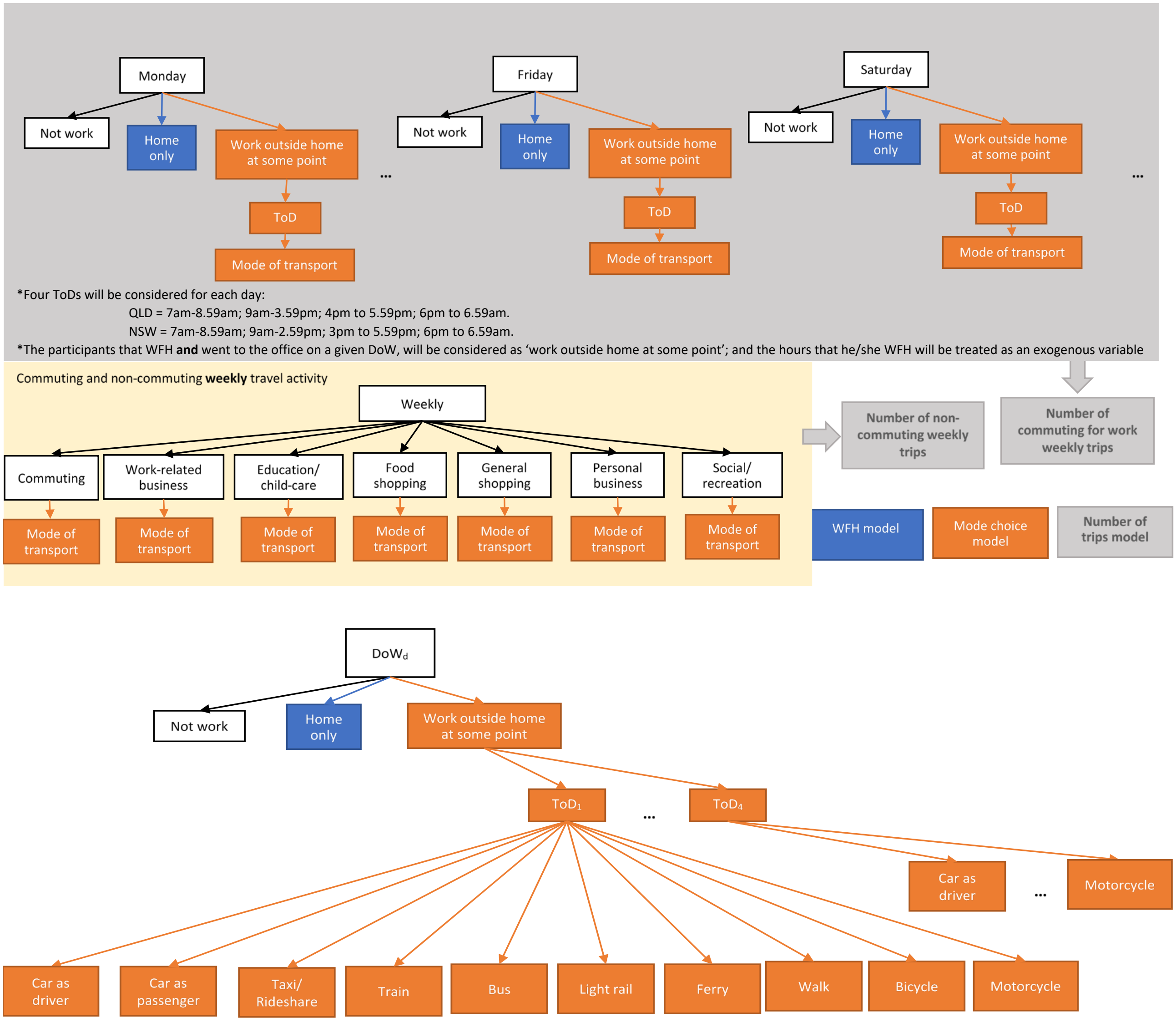


Figure 4: Model structure

The alternative of no work (alternative 1) is described by an alternative specific constant ASC and by respondents' socioeconomics z_n. The WFH alternative (alternative 2) is described by its alternative specific constant; respondents' socioeconomics; by dummy variables that represent each different day *d* of the week day_d; if the respondent works in the central business district area CBD_{work}; and by the distance from their home to their office $Dist_{Home-work}$. The utility functions are defined as follows:

$$U_{NoWork} = ASC_{NoWork} + \sum_n \beta_{NoWork,n} \cdot z_n \tag{1}$$

$$U_{WFH} = ASC_{WFH} + \sum_n \beta_{WFH,n} \cdot z_n + \sum_n \beta_{WFH,d} \cdot day_d + \beta_{WFH,CBD} \cdot CBD_{work} + \beta_{WFH,Dist} \cdot Dist_{Home-work} \tag{2}$$

where β 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_{Mode_m}; access time AcT_{Mode_m}; egress time EgT_{Mode_m}; waiting time WT_{Mode_m} and fare $Fare_{Mode_m}$, as shown in equation (3). Note that the parameter estimate β for access, egress and waiting times is generic[1].

$$\begin{aligned} U^{PT}_{Mode_m,ToD_t} = & ASC_{Mode_m} + ASC_{ToD_t} + \beta_{Mode_m,TT} \cdot TT_{Mode_m} + \beta_{Mode_m,Cost} \cdot Fare_{Mode_m} \\ & + \beta_{Mode_m,AEWT} \cdot \left(AcT_{Mode_m} + EgT_{Mode_m} + WT_{Mode_m} \right) \end{aligned} \tag{3}$$

The utility function for the car driver and motorcycle alternatives is described by travel time, fuel cost $Fuel_{Mode_m}$, parking cost $Park_{Mode_m}$, and toll costs $Toll_{Mode_m}$; as well as some socioeconomic characteristics[2], as presented in equation (4). Note that the parameter estimate β for fuel, toll and parking was estimated in the preferred model as generic[3].

$$\begin{aligned} U^{Car/moto}_{Mode_m,ToD_t} = & ASC_{Mode_m} + ASC_{ToD_t} + \beta_{Mode_m,TT} \cdot TT_{Mode_m} \\ & + \beta_{Mode_m,Cost} \cdot \left(Fuel_{Mode_m} + Park_{Mode_m} + Toll_{Mode_m} \right) + \sum_n \beta_{Mode_m,n} \cdot z_n \end{aligned} \tag{4}$$

The active modes (walk and cycling) and car passenger[4] alternatives are described only by the travel time, as presented in equation (5).

$$U^{Active}_{Mode_m,ToD_t} = ASC_{Mode_m} + ASC_{ToD_t} + \beta_{Mode_m,TT} \cdot TT_{Mode_m} \tag{5}$$

Table 1: Mixed Logit Model results for the GSMA, Wave 4 (June 2021)

Parameters	Acronym	Alternatives	Mean (std deviation)
Constants:			
ASC no work	ASC_NoWork	1	-
ASC work from home	ASC_WFH	2	-
ASC car driver/motorcycle	ASC_CarMoto	3, 12, 13, 22, 23, 32, 33, 42	-0.603 (3.28)
ASC car passenger	ASC_CarP	4, 13, 24, 34	-3.221 (14.19)
ASC taxi/ridesharing	ASC_Taxi	5, 15, 25, 35	-4.018 (6.66)
ASC public transport	ASC_PT	6-9, 16-19, 26-29, 36-39	-0.778 (3.69)
ASC active modes	ASC_Act	10, 11, 20, 21, 30, 31, 40, 41	-0.813 (3.50)
ASC ToD 1 and 3	ASC_T13	3-12, 23-32	0.216 (2.85)
ASC ToD 2	ASC_T2	13-22	-
ASC ToD 4	ASC_T4	33-42	0.451 (5.54)
Socio-economic variables:			
No Work - Age	Age_NW	1	0.021 (10.18)
Car driver - Number of cars in household	NCar_CarD	3, 13, 23, 33	0.155 (3.46)
WFH - Occupation professional (1,0)	OcProf_WFH	2	0.382 (3.03)

[1] They were estimated as specific first and the results suggested that they were not statistically different.
[2] The respondents' socioeconomics were tested in different modes of transport, but they were statistically significant only in the car driver mode.
[3] They were estimated as specific first and the results suggested that they were not statistically different.
[4] 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.

WFH - Occupation manager (1,0)	OcMng_WFH	2	0.574 (4.25)
WFH - Occupation clerical and administration (1,0)	OcAdm_WFH	2	0.623 (4.18)
WFH - Occupation blue collar worker (1,0)	OcBlCl_WFH	2	-0.670 (3.19)
Day of week:			
WFH - Monday dummy variable (1,0)	DMon_WFH	2	0.988 (6.96)
WFH - Tuesday dummy variable (1,0)	DTue_WFH	2	0.926 (6.47)
WFH - Thursday dummy variable (1,0)	DThu_WFH	2	0.700 (4.77)
WFH - Friday dummy variable (1,0)	DFri_WFH	2	0.717 (4.90)
Spatial location effects:			
WFH NSW - Wollongong residential location (1,0)	Woll_WFH	2	-1.234 (6.34)
WFH NSW - Newcastle residential location (1,0)	Newc_WFH	2	-0.868 (5.83)
WFH NSW - Central Coast residential location (1,0)	CentC_WFH		-0.780 (4.35)
Modal attributes:			
Travel time all modes except active - *mean*	TT_CarPT	3-9, 12-19, 22-29, 32-39, 42	-0.010 (3.15)
- *standard deviation*			0.008 (3.15)
Travel time walking	TT_Walk	10, 20, 30, 40	-0.040 (4.00)
Travel time bicycle	TT_Bike	11, 21, 31, 41	-0.013 (1.65)
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	-0.024 (2.75)
- *standard deviation*			0.024 (2.75)
Access + egress + waiting time taxi/PT modes	TTAEW	5-9, 15-19, 25-29, 35-39	-0.017 (0.94)
Number of parameters estimated			**26**
Sample size			**2,975**
Log Likelihood at convergence			**-4,897.17**
Log likelihood at zero			**-11,119.57**
McFadden Pseudo R squared			**0.56**
AIC/n			**3.31**

Table 2: WFH probability mapping model results (linear regression with 0-1 constraint) for the GSMA – Wave 4 Note: confidence intervals are available on request

Variable	Parameter Estimate (t test**)**
Constant	0.111 (21.69)
Socio-Economics	
At least one child in household attends primary school (1,0)	0.006 (2.29)
At least one child in household attends secondary school (1,0)	-0.010 (3.65)
Occupation Manager (1,0)	0.141 (28.26)
Occupation Professional (1,0)	0.107 (22.85)
Occupation Clerical and Administration (1,0)	0.148 (28.79)
Occupation Sales (1,0)	0.056 (11.11)
Occupation Community and Personal Services (1,0)	0.057 (10.44)
Occupation Labourer (1,0)	-0.019 (2.81)
Residential Location	
Home located in Newcastle (1,0)	-0.123 (46.95)
Home located in Illawarra (1,0)	-0.173 (56.53)
Home located in Central Coast (1,0)	-0.118 (39.76)
Workplace CBD of Sydney	

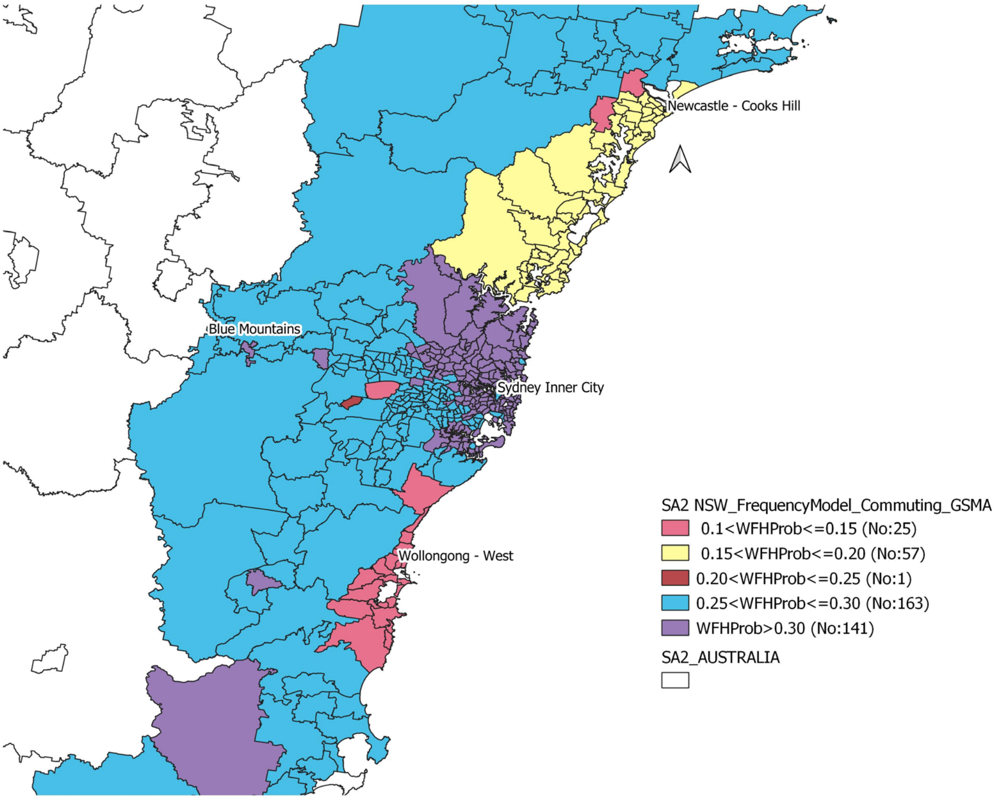
Work located in CBD area (1,0)	
Work located in Castle Hill area (1,0)	-0.043 (7.22)
Work located in North Sydney area (1,0)	0.066 (8.84)
Day of Week Commuting	
Monday dummy variable (1,0)	0.159 (47.56)
Tuesday dummy variable (1,0)	0.147 (44.40)
Thursday dummy variable (1,0)	0.105 (35.62)
Friday dummy variable (1,0)	0.108 (36.80)
Commuting Mode	
Main mode of transport to go to work now is PT (1,0)	0.010 (2.15)
Main mode of transport to go to work now is car driver (1,0)	-0.012 (4.67)
Number of weekdays commuting by Time of day	
Number of days a person commuted to work on ToD 1 (excluding weekends)	-0.013 (2.34)
Number of days a person commuted to work on ToD 2 (excluding weekends)	-0.015 (2.57)
Number of days a person commuted to work on ToD 3 (excluding weekends)	-0.026 (2.85)
Number of days a person commuted to work on ToD 4 (excluding weekends)	-0.028 (4.85)
Work place location characteristics	
Number of persons with occupation professionals in each workplace location NSW	0.000 (3.70)
Number of persons with occupation machinery operators and drivers in each workplace location NSW	0.005 (3.25)
Number of jobs in work postcode for Industry category (TMR industry categories provided by TMR) for Qld and NSW	-0.001 (2.95)
Number of jobs in work postcode for other category (TMR industry categories provided by TMR) for Qld and NSW	-0.011 (3.88)
Number of employees in business 20-199	0.008 (3.57)
Travel time for commuting	
Average daily travel time getting to work by car driver, car pax and motorcycle considering number of days a person commuted	0.000 (8.84)
Average daily travel time getting to work by PT considering number of days a person commuted	0.000 (6.48)
Average daily travel time getting to work by taxi / ridesharing considering number of days a person commuted in these modes	0.002 (4.29)
Sample size	***2,261***
Adjusted R squared	***0.86***

The next task is to build the evidence on WFH into MetroScan. Adjustments are required for each and every origin-destination pair in the 80 by 80 matrix. This is where the mapping equation is used, with a number of crucial variables providing the differentiation for a given origin of the probability of WFH. The number of commuting trips associated with each OD pair is adjusted down by the probability of WFH associated with each of the modes in the mapping equation, obtained by applying the levels of all explanatory variables associated with each origin and destination zone including the travel times for each OD pair and additional dummy variables for car and public transport as the chosen commuting mode. In addition, we have accounted for the number of jobs by occupation and industry as well as job density at the destination in order to provide a way of identifying a distribution of probabilities of WFH associated with a given origin across all destinations. The other key drivers of WFH relate to the socioeconomic characteristics of individuals and their households as well as some broad geographical location dummy variables such as Newcastle, Wollongong and the Central Coast compared to the Sydney Metropolitan area (SMA). Within the SMA, we also account for high density suburban shopping and employment precincts such as Castle Hill in the northwest and North Sydney in the lower north shore.

We also need to correct the number of trips by non-commuting purposes, which was identified from Poisson regression models (See Appendix C and middle panel of Figure 4 above) for the relationship between the number of one-way weekly trips and explanatory variables (Table C1), of which one was the proportion of working days that are worked from home. We obtained the direct elasticity estimates for the number of trips with respect to WFH, given as equations (6a-6g).

Education trips=Original ED trips*(1 + 0.077*WFH) (6a)
Food shopping=Original FS trips *(1+ 0.066*WFH) (6b)
General shopping=Original GS trips*(1+ 0.091*WFH) (6c)
Personal business=Original PB trips*(1+0.085*WFH) (6d)
Social/Recreational=Original SR trips*(1+0.053*WFH) (6e)
Care visit=Original CV trips*(1+0.019*WFH) (6f)
Work related = Original trips*(1-0.374*WFH) (6g)

Figure 5 and the associated table shows the average estimates of the probability of WFH for all workers regardless of commuting mode for each of the 80 zones in Metroscan. In addition, it summarises the probability of WFH for workers who use car or public transport when they commute.



SLAName	MScanZon	WFHProb	WFHProb_Car	WFHProb_PT	SLAName	MScanZor	WFHProb	WFHProb_	WFHProb_PT
Botany Bay (C)	1	0.290	0.281	0.303	Penrith (C) - East	41	0.283	0.274	0.296
Leichhardt (A)	2	0.308	0.299	0.321	Penrith (C) - West	42	0.283	0.274	0.296
Marrickville (A)	3	0.308	0.299	0.321	Blacktown (C) - North	43	0.285	0.275	0.297
Sydney (C) - Inner	4	0.308	0.299	0.321	Blacktown (C) - South-East	44	0.285	0.275	0.297
Sydney (C) - East	5	0.308	0.299	0.321	Blacktown (C) - South-West	45	0.285	0.275	0.297
Sydney (C) - South	6	0.308	0.299	0.321	Hunter's Hill (A)	46	0.317	0.308	0.330
Sydney (C) - West	7	0.308	0.299	0.321	Lane Cove (A)	47	0.315	0.306	0.328
Randwick (C)	8	0.306	0.297	0.319	Mosman (A)	48	0.319	0.310	0.332
Waverley (A)	9	0.311	0.302	0.324	North Sydney (A)	49	0.320	0.311	0.333
Woollahra (A)	10	0.293	0.284	0.306	Ryde (C)	50	0.305	0.296	0.318
Hurstville (C)	11	0.295	0.285	0.307	Willoughby (C)	51	0.314	0.304	0.326
Kogarah (A)	12	0.293	0.283	0.305	Hornsby (A) - North	52	0.306	0.296	0.319
Rockdale (C)	13	0.290	0.281	0.303	Hornsby (A) - South	53	0.306	0.296	0.319
Sutherland Shire (A) - East	14	0.299	0.290	0.312	Ku-ring-gai (A)	54	0.317	0.308	0.330
Sutherland Shire (A) - West	15	0.299	0.290	0.312	The Hills Shire (A) - Central	55	0.306	0.297	0.319
Bankstown (C) - North-East	16	0.284	0.275	0.297	The Hills Shire (A) - North	56	0.306	0.297	0.319
Bankstown (C) - North-West	17	0.278	0.269	0.291	The Hills Shire (A) - South	57	0.306	0.297	0.319
Bankstown (C) - South	18	0.284	0.275	0.297	Manly (A)	58	0.304	0.295	0.317
Canterbury (C)	19	0.284	0.275	0.297	Pittwater (A)	59	0.304	0.295	0.317
Fairfield (C) - East	20	0.272	0.263	0.285	Warringah (A)	60	0.304	0.295	0.317
Fairfield (C) - West	21	0.272	0.263	0.285	Gosford (C) - East	61	0.166	0.157	0.179
Liverpool (C) - East	22	0.282	0.273	0.295	Gosford (C) - West	62	0.166	0.157	0.179
Liverpool (C) - West	23	0.285	0.276	0.298	Wyong (A) - North-East	63	0.166	0.157	0.179
Camden (A)	24	0.289	0.280	0.302	Wyong (A) - South and West	64	0.166	0.157	0.179
Campbelltown (C) - North	25	0.279	0.270	0.292	Cessnock (C)	65	0.150	0.141	0.163
Campbelltown (C) - South	26	0.279	0.270	0.292	Lake Macquarie (C) - East	66	0.043	0.034	0.056
Wollondilly (A)	27	0.293	0.284	0.306	Lake Macquarie (C) - North	67	0.043	0.034	0.056
Ashfield (A)	28	0.308	0.299	0.321	Lake Macquarie (C) - West	68	0.043	0.034	0.056
Burwood (A)	29	0.294	0.285	0.307	Maitland (C)	69	0.278	0.269	0.291
Canada Bay (A) - Concord	30	0.310	0.300	0.322	Newcastle (C) - Inner City	70	0.167	0.158	0.180
Canada Bay (A) - Drummoyne	31	0.310	0.300	0.322	Newcastle (C) - Outer West	71	0.167	0.158	0.180
Strathfield (A)	32	0.291	0.282	0.304	Newcastle (C) - Throsby	72	0.167	0.158	0.180
Auburn (A)	33	0.291	0.282	0.304	Port Stephens (A)	73	0.155	0.146	0.168
Holroyd (C)	34	0.280	0.271	0.293	Kiama (A)	74	0.120	0.111	0.133
Parramatta (C) - Inner	35	0.300	0.291	0.313	Shellharbour (C)	75	0.104	0.095	0.117
Parramatta (C) - North-East	36	0.300	0.291	0.313	Wollongong (C) - Inner	76	0.120	0.111	0.133
Parramatta (C) - North-West	37	0.300	0.291	0.313	Wollongong (C) Bal	77	0.120	0.111	0.133
Parramatta (C) - South	38	0.280	0.271	0.293	Shoalhaven (C) - Pt A	78	0.108	0.098	0.121
Blue Mountains (C)	39	0.295	0.286	0.308	Shoalhaven (C) - Pt B	79	0.108	0.098	0.121
Hawkesbury (C)	40	0.283	0.273	0.295	Wingecarribee (A)	80	0.293	0.283	0.305

Figure 5: WFH probability by Location June 2021

We see in Figure 5 that the highest incidence of working from home is predicted to occur in locations closer to the Centre of Sydney and generally in the wealthy locations where there is a higher accumulation of workers in professional and managerial occupations who are more likely to be able to WFH. The locations depicted with lower probabilities of WFH are heavily populated with blue collar workers and those who jobs prevent WFH. This evidence lines up well with that from other studies such as the recent Productivity Commission study (2021).

In addition to the adjustment of the number of commuting and non-commuting trips associated with modes and times of day, we also have to account for any changes in the travel times on the road network as a result of levels of WFH. The way do this is to use an adjustment equation for each and every trip purpose that adjusts the initial travel time before further traffic assignment[5]. The adjustment models are given in equations (7a-7c) where we initially obtained predictions of trips accounting for WFH (e.g., newavgtrips) and not accounting for WFH (oldavgtrtips), given the latter is resident in the network levels of performance data base, and then applied these formula to obtain travel times in the presence of the incidence of WFH. Importantly the travel times are adjusted as the number of trips varies.

new avgtime = base avgtime*(1+*0.3535*(newavgtrips/oldavgtrips - 1)) (7a)
new peaktime = base peaktime*(1+*0.739*(newpeaktrips/oldpeaktrips - 1)) (7b)
new offpeaktime = base offpeaktime*(1+*0.196*(newoffpeaktrips/oldoffpeaktrips - 1)) (7c)

[5] MetroScan uses its own internal traffic assignment routines linked to the open-source traffic assignment platform PLANit (https://github.sydney.edu.au/PLANit), developed at ITLS (University of Sydney). The assignment configuration conducts a traditional static traffic assignment where route choice and network loading is done by deterministic user equilibrium (DUE) with the shortest path algorithm as Dijkstra one-to-all. Smoothing uses the method of successive averages (MSA) with the number of iterations user configurable; when set to 1 (default), DUE collapses to an all-or-nothing (AON) assignment.

4. Impact of accounting for WFH on the base or status quo situation

The starting position for assessing the impact of WFH is to compare a base or status quo situation where we ignore WFH (essentially a pre-COVID-19 situation with negligible WFH) to a base with WFH in mid-2021. The most interesting empirical evidence is summarised in Table 3 for the year 2023 with spatially distributed impact changes associated with residential and workplace locations, and with modal shares for all 80 zones summarised in Figures 6 to 8.

Overall, we see an an annual reduction of 113.5 million trips (or 2.2% drop) in the number of annual trips by car and public transport for all trip purposes, with the greatest percentage decline being in public transport (~9%). This translates into a modal shift into the more bio-secure car compared to public transport, with car increasing from 91.33% to 91.92% for all trip purposes. This has resulted in an annual revenue loss to public transport of 8.75% (from $1.482bn to $1.352m). Although the motorised modal share in favour of the car increased, there was a noticeable decline in car use which resulted in a reduction in fuel excise (4.85%), toll revenue (2%) and parking revenue (0.33%).

The generalised cost of public transport and car travel in $/person trip is based on all the components of time and cost and associated valuation given in Appendix B. It is a comprehensive set of factors for main mode travel time, access and egress time, public transport headways, travel time variability, crowding on public transport, number of transfers and all cost components (fares, fuel, tolls, parking). There are noticeable decreases in generalised cost outlays associated with WFH, as might be expected where we account for the reduction in commuting travel as well as any changes in non-commuting as a result of WFH, of which some trip purpose activity might increase as a result of more flexible working arrangements. The extent of change associated with each trip purpose is discussed in Balbontin et al. (2021) for all trip purposes and Hensher, Beck et al. (2021) for details on commuting travel time and cost savings and how that saving is reallocated to work (paid and unpaid)and leisure). On average, we see a $0.146 decrease in the generalised cost for public transport and $0.89 for car travel, resulting in a weighted average reduction in the generalised cost of car and public transport of 3.75%.

Table 3 Summary of key MetroScan outputs with and without accounting for WFH, 2023

Modal Activity per annum (all trip purposes):	Base (before WFH)	Allowing for WFH	Percentage change
Car drive alone	3,063,173,050	2,970,069,248	-3.039
Car with passengers	1,650,606,668	1,669,612,761	1.151
Bus	194,705,461	178,345,562	-8.402
Train	252,787,164	229,722,719	-9.124
Total motorised modes	*5,161,272,343*	*5,047,750,290*	*-2.199*
Modal shares (all trip purposes):			
Car drive alone	59.35%	58.84%	-0.859
Car with passengers	31.98%	33.08%	3.427
Bus	3.78%	3.53%	-6.411
Train	4.90%	4.55%	-7.122
Passenger Vehicles:			
Total daily car kms	252,725,288	225,630,166	-4.848
Total revenue for PT use ($pa)	1,482,019,696	1,352,421,896	-8.745
Total revenue from parking ($pa)	302,715,424	301,733,633	-0.325
Total government revenue for GST	64,381,101,223	61,259,401,088	-4.848
Total revenue from toll roads ($)	867,317,568	849,985,927	-1.998
Total annual auto VKM ($)	9,165,032,041	8,720,639,491	-4.848
Total government revenue from fuel excise ($pa)	3,302,013,595	3,141,906,108	-4.848
Generalised cost per annum for PT ($pa)	9,726,699,697	8,806,113,504	-9.423
Generalised cost per annum for car ($pa)	104,504,496,348	98,546,845,871	-5.53
Generalised cost per person trip for PT ($)	21.726	21.58	-0.672
Generalised cost per person trip for car ($)	22.13	21.24	-4.022
Generalised cost per person trip car & PT ($)	22.095	21.267	-3.745

Freight Vehicles:			
Total government revenue from fuel excise ($pa)	1,162,090,474	1,168,269,296	0.532
Annual Total distance travelled Articulated	3,478,798,038	3,497,879,878	0.549
Annual Total distance travelled Rigid	2,331,654,333	2,343,466,600	0.507
Generalised cost per trip for freight ($)	126,303	123,487	0.532
Emissions and Pollution:			
Total CO_2 for passenger and freight movements	16,746,997,718	16,144,193,943	-3.599
Total CO_2 for passenger movements	12,432,062,391	11,829,258,616	-4.849
Total annual carbon dioxide for trucks	4,314,935,327	4,337,961,459	0.534
Total annual local air pollution costs for trucks	2,674,467,833	2,688,976,524	0.542

Emission impacts are of particular interest in a de-carbonisation world. We see an aggregate reduction in CO_2 of 3.60% for passenger and freight modes, of which passenger movements is the greatest contributor with a 4.85% reduction, but associated with a truck increase of 0.53%, the latter largely due to greater freight distribution during the pandemic including the growth in online shopping and delivery by light commercial vehicles.

Figures 6 and 7 show that there is a greater incidence of reduced trips associated with the incidence of WFH in locations close to the Central area of Sydney (but up to 20 kilometres in most directions) including close by suburbs that are relatively wealthy and have a high proportion of people in occupations where WFH is feasible and achievable. While we see a consistent decrease in overall annual trips by all purposes this declines the further north and south where essential workers are more prevalent.

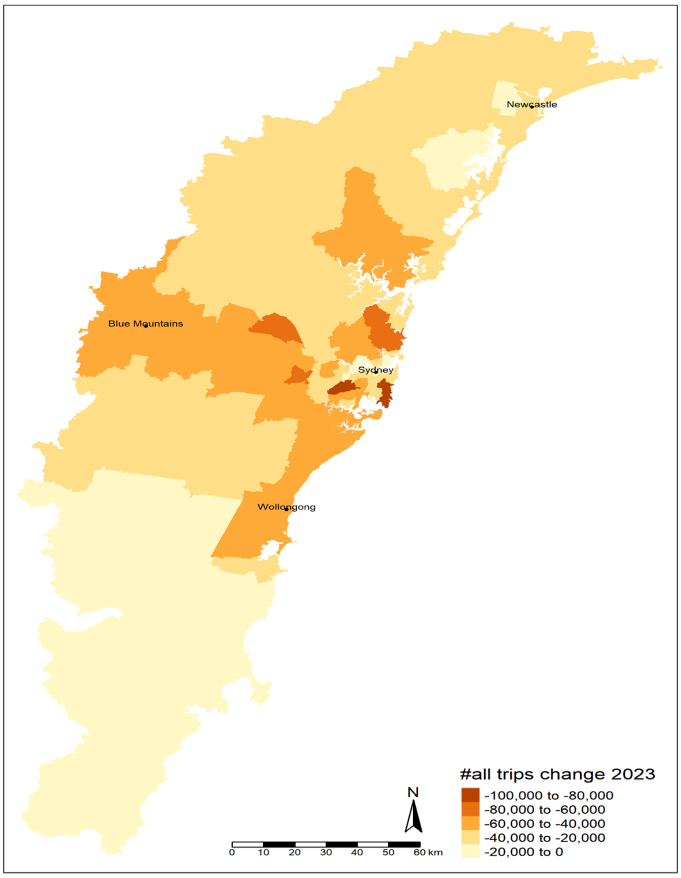


Figure 6: Impact of WFH on total trips 2023

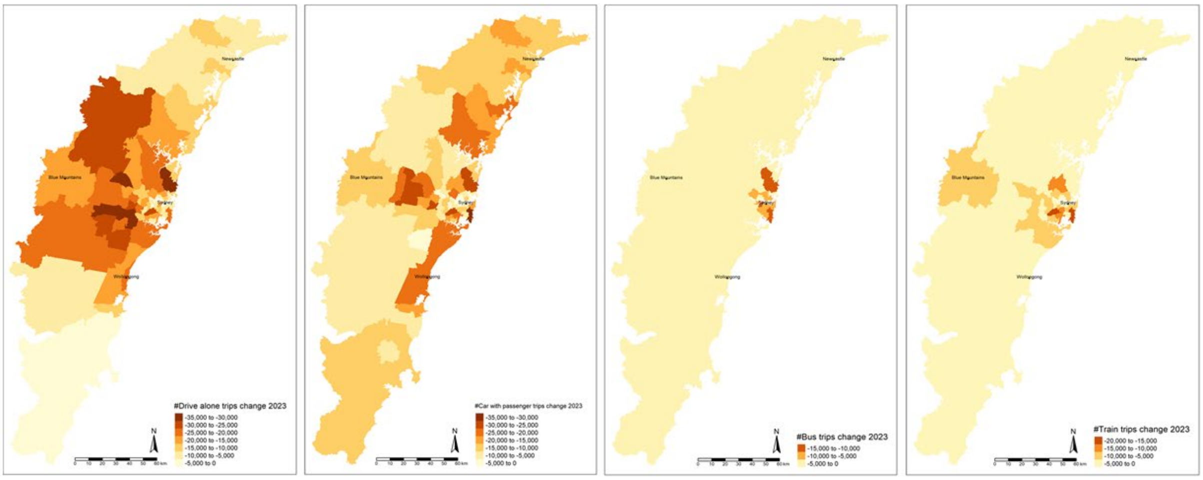


Figure 7: Impact of WFH on modal usage 2023

It is expected that WFH will impact of residential and workplace locations choices. In Metroscan this is influenced by changing levels of service associated with mode and time of days travel which results in a linked logsum (or expected maximum utility change) out of the mode and time of day model that is carried forward into location choice models representing changes in accessibility between each origin and destination zonal pair. These links are given in more detail in Figure 8, building on Figure 2.

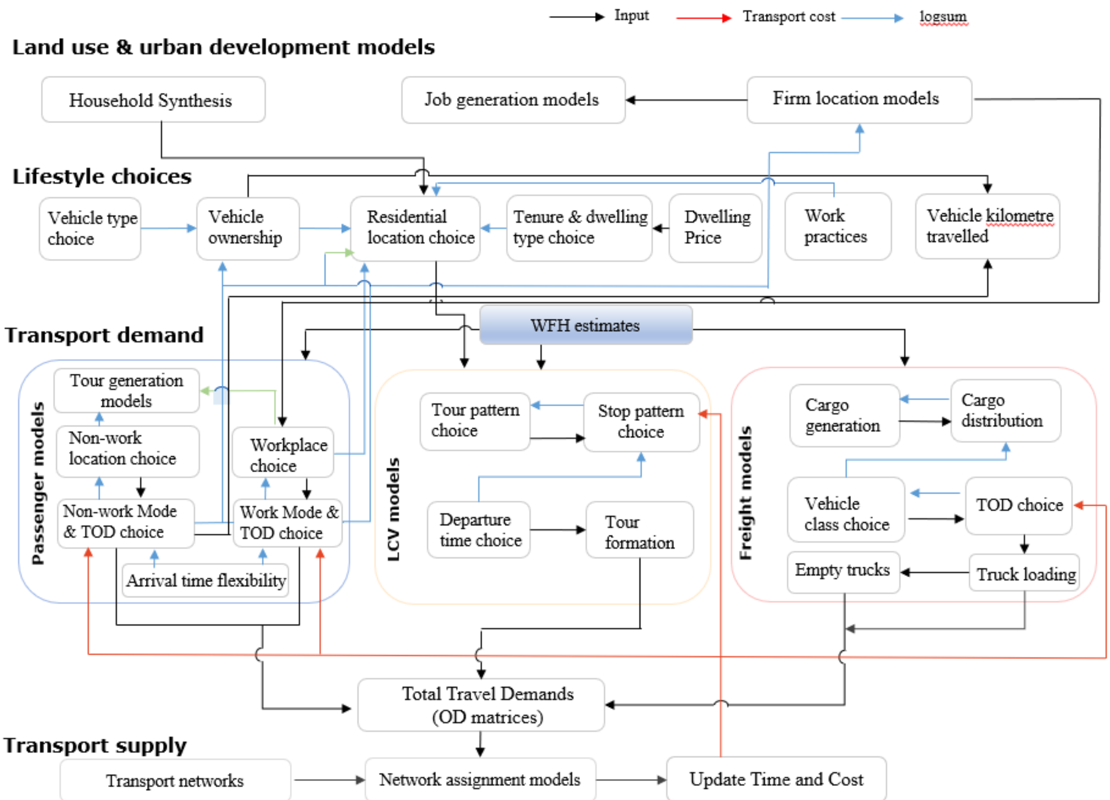


Figure 8: Tracing changes in accessibility on location responses

We can see the changes in workplace (left hand side) and residential (right hand side) locations as a result of increased WFH in 2023 and 2033. We present forecasts 12 years out as well as in 2023 to emphasise that these location adjustments take time and in the immediate years we anticipate relatively little change but more change in later years as people start to adjust their housing and job prospects. In general, we see growth of residential and workplace locations away from central areas within the GSMA which aligns with what is being shown in surveys of plans by employers and employees to move to satellite offices and reduced commuting travel and hence associated residential locations further out under the predicted suburbanisation trend (Beck and Hensher 2021b). But this takes time, and by 2033 we start to see significant reductions in people working in the central parts of Sydney, the Central coast and Newcastle as well as a start of a suburbanisation trend. Given the impacts that including WFH in a strategic transport and location model system has, the next task is to extend the analysis to an investment in a large piece of road infrastructure to see if the justification is tempered by the growth in WFH.

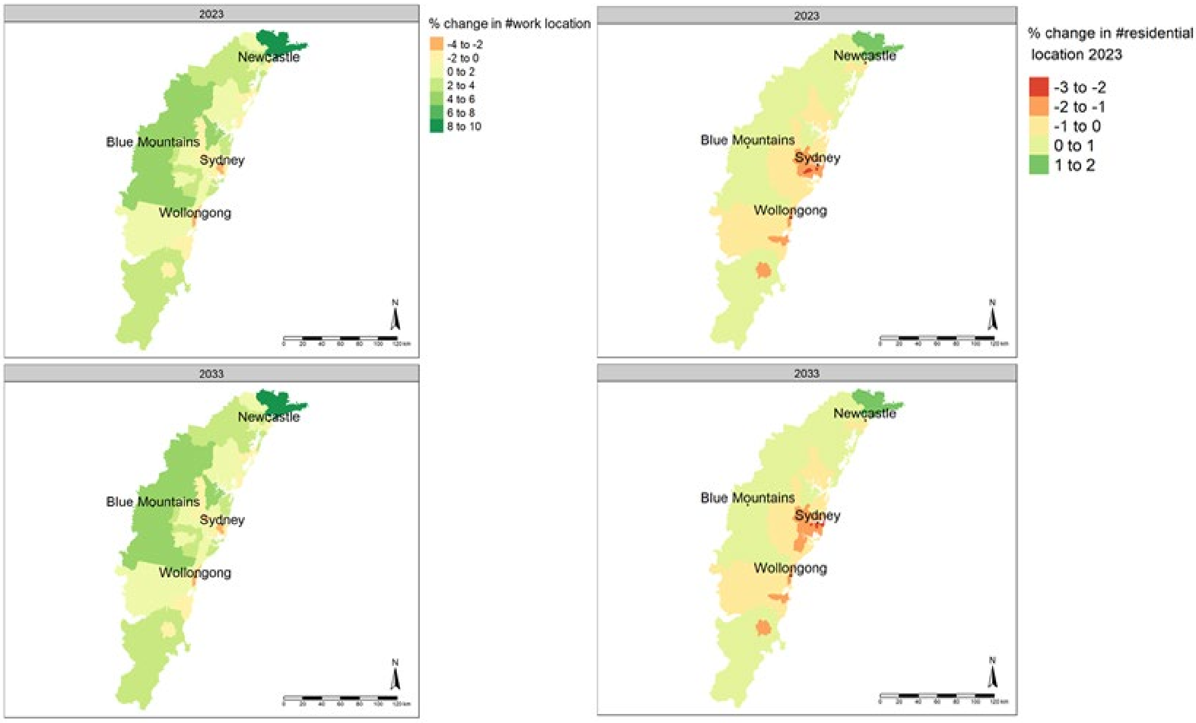


Figure 9: Impact of WFH on workplace and residential location

5. A Motorway Case Study

The Sydney case study selected is the M4 Outer Motorway upgrade (Figure 10) as representative of major road projects. This is a road widening project of around 37 kilometres in length, from the M4 East to the Nepean River, as shown in purple in Figure 10 (and between Parramatta and the Blue Mountains in Figure 3). This project is also estimated to have a capital cost of around $2.4 billion.

Figure 10: M4 Outer Motorway (Source: Western Sydney road alignments - M4 Motorway (Sydney) - Wikipedia

We have two scenarios of interest to compare with Table 3, namely the introduction of the M4 motorway before allowing for WFH and after allowing for WFH (Table 4), and the impact of the M4 when WFH is not considered at all (Table 5). In another paper, we report the results of this assessment where we ignore WFH (Stanley et al. 2021). While the impact on WFH or not in the presence of the M4 extensions is significant, a comparison between Table 3 and 4 suggests that the impact of the M4 investment on the overall performance of the network is negligible compared to the impact that WFH has since the levels of changes in both tables are very close, again reinforcing the enormous importance of WFH as a transport policy lever in obtaining significant positive change in network performance and emissions, despite the loss of public transport trips. Table 5 provides the comparison between investing in the M4 motorway and not doing so when we ignore WFH in our modelling and assumes the levels of WFH observed during the pandemic (in June 2021) did not occur. The most notable impact of the M4 in this setting is improvement in the generalised cost of freight vehicle movements (2.12%), associated in part with increased online shopping and the growth in demand of food etc.; otherwise it reinforces what is said above when comparing the evidence in Tables 3 and 4.

Table 4: Predicted impact of the M4 outer motorway before after allowing for WFH

Modal Activity per annum (all trip purposes):	In absence of WFH	Allowing for WFH	Percentage change
Car drive alone	3,066,126,672	2,972,907,623	-3.04
Car with passengers	1,649,450,071	1,668,415,118	1.15
Bus	193,875,141	177,576,210	-8.407
Train	250,592,807	227,683,299	-9.142
Total motorised modes	5,160,044,691	5,046,582,250	-2.199
Modal shares (all trip purposes):			
Car drive alone	59.421	58.909	-0.862
Car with passengers	31.966	33.06	3.422
Bus	3.757	3.519	-6.335
Train	4.856	4.512	-7.084
Passenger Vehicles:			
Total daily car kms	252,750,626	240,500,210	-4.847
Total revenue for PT use ($pa)	1,472,595,406	1,343,672,397	-8.755
Total revenue from parking ($pa)	302,821,676	301,838,504	-0.325
Total government revenue for GST	64,387,555,812	61,266,794,784	-4.847
Total revenue from toll roads ($)	867,384,304	850,059,061	-1.997
Total annual auto VKM ($)	9,165,950,891	8,721,692,028	-4.847
Total government revenue from fuel excise ($pa)	3,302,344,641	3,142,285,320	-4.847
Generalised cost per annum for PT ($pa)	9,644,954,472	8,795,503,729	-8.807

Generalised cost per annum for car ($pa)	104,002,045,067	98,212,788,767	-5.566
Generalised cost per person trip for PT ($)	21.7	21.554	-0.673
Generalised cost per person trip for car ($)	22.055	21.168	-4.022
Generalised cost per person trip car & PT ($)	22.024	21.199	-3.746
Freight Vehicles:			
Total government revenue from fuel excise ($pa)	1,167,967,975	1,173,399,026	0.465
Annual Total distance travelled Articulated	3,496,949,142	3,514,853,522	0.512
Annual Total distance travelled Rigid	2,342,890,733	2,353,949,177	0.472
Generalised cost per trip for freight ($)	123.624	121.028	-2.1
Emissions and Pollution:			
Total CO2 for passenger and freight movements	16,770,147,304	16,167,524,872	-3.576
Total CO2 for passenger movements	12,433,308,779	11,830,686,347	-4.847
Total annual carbon dioxide for trucks	4,336,838,525	4,357,265,034	0.471
Total annual local air pollution costs for trucks	2,688,268,896	2,701,307,000	0.485

Table 5: Predicted impact of the M4 outer motorway compared to no project under no allowance for WFH

	Status Quo (no Projects)	M4 Motorway	Base vs M4 no WFH
Modal Activity per annum (all trip purposes):	Base (before WFH)	In absence of WFH	Percentage change
Car drive alone	3,063,173,050	3,066,126,672	0.096
Car with passengers	1,650,606,668	1,649,450,071	-0.070
Bus	194,705,461	193,875,141	-0.426
Train	252,787,164	250,592,807	-0.868
Total motorised modes	*5,161,272,343*	5,160,044,691	-0.024
Modal shares (all trip purposes):			
Car drive alone	59.350	59.421	0.120
Car with passengers	31.980	31.966	-0.044
Bus	3.775	3.757	-0.477
Train	4.900	4.856	-0.898
Passenger Vehicles:			
Total daily car kms	252,725,288	252,750,626	0.010
Total revenue for PT use ($pa)	1,482,019,696	1,472,595,406	-0.636
Total revenue from parking ($pa)	302,715,424	302,821,676	0.035
Total government revenue for GST	64,381,101,223	64,387,555,812	0.010
Total revenue from toll roads ($)	867,317,568	867,384,304	0.008
Total annual auto VKM ($)	9,165,032,041	9,165,950,891	0.010
Total government revenue from fuel excise ($pa)	3,302,013,595	3,302,344,641	0.010
Generalised cost per annum for PT ($pa)	9,726,699,697	9,644,954,472	-0.840
Generalised cost per annum for car ($pa)	104,504,496,348	104,002,045,067	-0.481
Generalised cost per person trip for PT ($)	21.726	21.7	-0.120
Generalised cost per person trip for car ($)	22.13	22.055	-0.339
Generalised cost per person trip car & PT ($)	22.095	22.024	-0.321
Freight Vehicles:			
Total government revenue from fuel excise ($pa)	1,162,090,474	1,167,967,975	0.506
Annual Total distance travelled Articulated	3,478,798,038	3,496,949,142	0.522
Annual Total distance travelled Rigid	2,331,654,333	2,342,890,733	0.482
Generalised cost per trip for freight ($)	126	123.624	-2.121

Emissions and Pollution:			
Total CO_2 for passenger and freight movements	16,746,997,718	16,770,147,304	0.138
Total CO_2 for passenger movements	12,432,062,391	12,433,308,779	0.010
Total annual carbon dioxide for trucks	4,314,935,327	4,336,838,525	0.508
Total annual local air pollution costs for trucks	2,674,467,833	2,688,268,896	0.516

6. Conclusions

The modelling capability developed and presented in this paper provides a behaviourally appealing way of recognising the incidence of working from home over a week and the appeal of embedding it into an integrated strategic transport and land use model system. The focus is on a capability to identify levels of WFH at a spatial level; in our model system it is an 80 by 80 origin-destination zonal level for the entire GSMA in NSW. The major changes that are associated with WFH are the quantum of commuting trips as well a non-commuting trips, where the latter is in part a response to more flexible working hours over a 24/7 week and the ability to undertake non-commuting trips when commuting travel time is 'saved'. Hensher et al. (2021) show that approximately 50% of the time reallocated from reduced commuting is used for leisure activities out of home and hence we see increased non-commuting trip making.

We have accounted for these changes and tracked them through Metroscan to obtain changes in travel times on the road network, which have impacts on many travel and locations choices, including over a 10 year period up to 2033, some amount of residential and workplace relocation (Figure 9). The feedback relationships between the full set of behavioural choices set out in Figures 2 and 8 enable us to gain a better understanding of just where changes in the probability of WFH have a spatial impact.

The most noteworthy changes in the transport sector as a result of the growing incidence of WFH, regardless on any proposed new transport initiatives, as identified in Metroscan, are reduced CO_2 emissions (up to 10%), close to a 13% reduction in the generalised cost of travel for all motorised modes, which is equivalent to an average saving of around \$1 per person one-way trip, and a 16% reduction in total annual one-ways trips by all motorised modes with public transport having the greatest reduction of around 37%. Freight vehicle movement, however, has increased by half a percent which is substantial. When we introduce a project, the M4 outer motorway, the changes in key policy outputs are very small compared to the introduction of WFH in Metroscan.

In ongoing research, we are continuing to re-assess the evidence on the impact of WFH as we use the next waves of data collected to obtain new parameter estimates for mapping WFH with the variables describing each origin and destination. It is clear that WFH is possibly the most impactful, in a positive sense, transport policy lever we have had since the advent of the car. We are hoping to identify some stability in the estimates of the parameters as a way of giving us confidence that the 'next normal' under increased WFH is a solid reference point in going forward in analysis as part of both 'predict and provide' and 'vision and validate' (Jones 2016)[6]. While some authors have asked whether "predict and provide" might be a welcome casualty of COVID-19 and finally be replaced with a more holistic 'vision and validate' approach, focused on the kind of towns and cities we want to live in, and not ones that

[6] 'Vision' is the setting out and planning from the outset what we want 'inspiring, sustainable growth' to look like. 'Validate' utilises exemplar design and modal shift forecasting techniques to test that vision, ensuring that our efforts will lead us to the best ways of eventually achieving it. This would envision, for example, what we want 'good growth' to look like, and use forecasting and design skills to test scenarios in order to identify the approach which will provide us with the best opportunity of achieving that vision.

simply deal with residual traffic impacts, we would suggest that both perspectives have merit in a linked way. Specifically, the analytical tools that are commonly associated with 'predict and provide' should be repositioned to be responsible in recognising the types of initiatives that align with 'vision and validate', and hence can add value in understanding the varied sets of output results that can be used to judge a range of scenario-based futures where vison is key driver. The old 4-step model that is a villain in the 'predict and provide' armoury could well be replaced with tools such as Metroscan that provide enrichment support for obtaining relevant information of consequence on behavioural change.

Appendix A: Descriptive Statistics for the commuter mode choice and mapping equations

Table A1: Descriptive profile of respondents Wave 4 - mean (standard deviation)

Variables	GSMA
Age	41.54 (14.7)
Average personal annual income (AUD$000)	83.88 (52.8)
Number of people in the same house	3.21 (1.4)
Number of cars in your household	2.63 (1.0)
Number of children in household	0.66 (0.9)
Number of modes available	4.95 (2.7)
Proportion who used car as driver to commute prior to COVID-19	0.693
Distance from home to regular workplace location (kms)	19.95 (20.2)
Proportion of sample who are blue collar workers	0.154
Proportion of workers who have a high level of concern about using PT	0.379
Occupation professional (1,0)	0.287
Occupation manager (1,0)	0.192
Occupation sales (1,0)	0.095
Occupation clerical and administration (1,0)	0.181
Occupation community and personal services (1,0)	0.090
Occupation technology (1,0)	0.052
Occupation machine operators (1,0)	0.050
Occupation labourers (1,0)	0.052
NSW - Wollongong residential location (1,0)	0.138
NSW - Newcastle residential location (1,0)	0.192
NSW – Central Coast residential location (1,0)	0.119
QLD – Gold Coast residential location (1,0)	-
QLD – Sunshine Coast residential location (1,0)	-
Work located in CBD (1,0) (SEQ=4000, 4006 postcodes; GSMA = 2000, 2007, 2009 and 2011 postcodes)	0.128
Number of respondents	**421**
Number of observations (respondents-day of week)	**2,947**

Table A2: Mode characteristics Wave 4- mean (standard deviation)

Variables	GSMA
Travel time car driver (min)	29.24 (21.1)
Travel time car pax (min)	27.18 (19.2)
Travel time taxi/ride share (min)	25.56 (14.1)
Travel time train (min)	43.95 (34.3)
Travel time bus (min)	38.60 (29.5)
Travel time light rail (min)	47.50 (24.7)
Travel time ferry (min)	30.00 (10.0)
Travel time walk (min)	25.57 (16.9)
Travel time bicycle (min)	34.20 (29.4)
Travel time motorcycle (min)	36.67 (31.4)
Fuel car driver (AUD$)	3.85 (3.7)
Fuel car pax (AUD$)	3.40 (3.1)
Fuel motorcycle (AUD$)	1.60 (1.3)
Parking car driver (AUD$)	1.87 (7.4)
Parking car pax (AUD$)	0.17 (1.3)
Toll car driver (AUD$)	1.43 (9.0)

Variables	GSMA
Toll car pax (AUD$)	0.25 (1.6)
Waiting time train (min)	7.67 (4.9)
Waiting time bus (min)	7.92 (5.1)
Waiting time light rail (min)	5.00 (0.0)
Waiting time ferry (min)	8.33 (2.9)
Egress time train (min)	9.56 (5.1)
Egress time bus (min)	8.08 (5.4)
Egress time light rail (min)	12.50 (3.5)
Egress time ferry (min)	5.67 (4.0)
Access time train (min)	13.43 (10.3)
Access time bus (min)	12.83 (16.1)
Access time light rail (min)	8.50 (2.1)
Access time ferry (min)	20.00 (10.0)
Ride Share fare ($)	33.44 (31.1)
Train Fare ($)	6.56 (5.4)
Bus Fare ($)	4.81 (4.8)
Light Rail Fare ($)	21.00 (12.7)
Ferry Fare ($)	15.50 (20.4)

Appendix B: Generalised Cost and Emission Calculations

Public Transport Times

Bus Time=In Vehicle Time + 1.5*Egress Time + 4.1 *STD of In Vehicle Time +1.5*Access Time +1.65*STAND + 0.7* Peak Time Frequency (Headway Minutes)

Train Time=In Vehicle Time + 1.5*Egress Time + 4.1 *STD of In Vehicle Time +1.5*Access Time +1.65*STAND + 0.7* Peak Time Frequency (Headway Minutes) + 1.5*Transfer Times

GC for Bus and Train

$$BusGC = \sum_{i=1}^{6}\sum_{j=1}^{6} Bustime * VoT$$

$$TrainGC = \sum_{i=1}^{6}\sum_{j=1}^{6} Traintime * VoT$$

with i for the commuting, business, and other non-work trips, and j as 6 time of the day (TOD).

Car Peak Time and Car Off-Peak Times

Carotime = Off-Peak in vehicle time + 1.5 * Egress Time + 4.1*STD of In Vehicle Time

Carptime = Peak in vehicle time + 1.5 * Egress Time + 4.1*STD of In Vehicle Time

GC for Bus and Train

$$CarPGC = \sum_{i=1}^{6}\sum_{j=1}^{6} (Carptime * VoT\ +\ Other\ Costs)$$

$$CarOpGC = \sum_{i=1}^{6}\sum_{j=1}^{6} (Carotime * VoT\ +\ Other\ Costs)$$

Note: VOT is different for commuting and other purposes as noted in the following table and varies by purpose (i) and time of the day (TOD, j). The peak and off-peak times are weighted averaged based on the amount of peak and off-peak time to obtain the overall GC for car.

Public Transport	All by ToD				VoT weight	Row	VoT
Variable in these utility expressions	Bus	Train	Walk	Cycle			

INVTIME = in-vehicle time in minute	√	√	√	√	1	OD	17.72/57.49
EGGTIME = egress time in minute walking propn	√	√			1.5	O or D	
DEVTIME2 = std dev of door-to-door travel time in minute	√	√			4.1	OD	
ACCTIME = access time in minute walking propn	√	√			1.5	O or D	
FARE = PT fare (one way) in $	√	√			N/A	OD	
STAND = number of people stand on PT when boarding	√	√			1.65	OD	
PTFREQ = PT frequency (or headway) in minute	√	√			0.93 to 0.37*	OD	
MABUS = access mode is bus (1/0)		√			N/A	O or D	
MEPT = egress mode is PT (1/0)					N/A	O or D	
TRANSFER = number of transfers		√			1.5	OD	
MACAR = access mode is car (1/0)	√	√			N/A	O or D	
* 5 min service =0.93, 10 min=0.83, 20 min=0.65, 30 min=0.52, 40 min= 0.44, 60 min = 0.37							
GC = sum of all after applying adjusted VoT to levels of each attribute							

Car	All by toD		VoT weight	Row	VoT
Variable in these utility expressions	Car DA	Car RS			
INVTIME = in-vehicle time in minute	√	√	1	OD	17.72/57.49
GGTIME = egress time in minute walking propn	√	√	1.5	O or D	
DEVTIME2 = std dev of door-to-door travel time in minute	√	√	4.1	OD	

Walk and Cycle	All by ToD		VoT weight		VoT
Variable in these utility expressions	Walk	Cycle		Row	
INVTIME = in-vehicle time in minute	√	√	N/A	OD	23.49
Using value of $3.25/trip travelling 8.3 mins on average, the VoT for walk per hour is $23.49 (3.25/8.3*60).					

Other costs include parking, toll, fuel, registration and maintenance costs are shown in the following table for each trip purpose.

	Km	trip parking cost	trip toll cost	Trip fuel cost	Rego	Maintenance	Total costs/trip	Weight based on trips
Commuting	15.7	$1.33	$1.02	$2.79	$0.94	$2.51	$8.59	0.17
Work related business	16.4	$1.39	$1.07	$2.91	$0.98	$2.62	$8.97	0.063
Education/childcare	6.3	$0.53	$0.41	$1.12	$0.38	$1.01	$3.45	0.1
Shopping	5.5	$0.46	$0.36	$0.98	$0.33	$0.88	$3.01	0.154
Personal business	7	$0.59	$0.46	$1.24	$0.42	$1.12	$3.83	0.055
Social/recreation	8.4	$0.71	$0.55	$1.49	$0.50	$1.34	$4.60	0.253
Serve passenger	5.8	$0.49	$0.38	$1.03	$0.35	$0.93	$3.17	0.182
Other	4.7	$0.40	$0.31	$0.83	$0.28	$0.75	$2.57	0.022
Weighted average total	**8.85**	**$0.75**	**$0.58**	**$1.57**	**$0.53**	**$1.42**	**$4.84**	

Other key assumptions used in MetroScan are given below.

	Commute	Non-commute	Business	Freight	LCV

	Car	PT	Car	PT	Car	PT		
VTTS per person ($/person hour)	17.72	17.72	17.72	17.72	57.48	57.48	31.05	25.41
Average vehicle occupancy	1.7		1.7		1.3		1	1
Value of travel time reliability (VoR) ($/person hour)*	30.12	Bus only	30.12	Bus only	97.72	97.72	52.79	52.79
Value of out-of-vehicle time ($/person hour)	26.58	26.58	26.58	26.58	57.48	57.48	N/A	N/A
CO_2 emissions (c/km)	2.66	15.61 bus; 0.8 rail; 32.69 light rail	2.66	15.61 bus; 0.8 rail; 32.69 light rail	2.66	15.61 bus; 0.8 rail; 32.69 light rail	3.67 rigid, 14.64 articulated	2.35
Air pollution (c/vkm)	3.37	37.9 bus; 4.99 rail; 41.42light rail	3.37	37.9 bus; 4.99 rail; 41.42light rail	3.37	37.9 bus; 4.99 rail; 41.42light rail	16.5 rigid, 65.82 articulated	7.56
Air pollution (c/pkm)	2.39	1.89 bus, 0.04 train, 0.64 LR	2.39	1.89 bus, 0.04 train, 0.64 LR	2.39	1.89 bus, 0.04 train, 0.64 LR	N/A	N/A
Carbon dioxide equivalent (CO2-e) $/tonne*	62.79							
Carbon monoxide (CO) $/tonne*	3.95							
Oxides of nitrogen (Nox) $/tonne*	2.503.55							
Particulate matter (PM10) $/tonne*	398,451.75							
Total hydrocarbons (THC) $/tonne*	1,254.41							
Fuel excise (proportion of fuel price)	0.416							

*Transport for NSW (2020)

Appendix C: Poisson Regression Models for One-way weekly trips for each trip purpose

A Poisson regression model is estimated for the number of one-way weekly trips for each purpose type, location (metropolitan or regional area) and working status in June 2021. In total, 8 models were estimated for the workers in the GSMA. The dependent variables, the number of one-way weekly trips for each purpose, are non-negative discrete count values, with truncation at zero, which are defined as a discrete random variable, y_i, observed over one period of time. The Poisson regression probability is given by equation (C1).

$$P(y_i = k \mid \mu_i) = \frac{\exp(-\mu_i) \cdot \mu_i^{k}}{k!} \qquad k = 0,1,\ldots \tag{C1}$$

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

$$\mu_i = E(y_i = k \mid x_i) = \exp(\beta' x_i) \tag{C2}$$

The prediction rate or expected frequency of the number of days WFH was calculated as a function of different explanatory variables, shown in equation (C3).

$$\mu_i = \exp\left(\beta_0 + \sum_n \beta_n \cdot z_n \cdot d_a + \sum_m \beta_m \cdot x_m \cdot d_a + \sum_f \beta_f \cdot x_f + \varepsilon\right) \tag{C3}$$

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

The direct point elasticities are presented in equation (C4).

$$\text{Elasticity} \Rightarrow \frac{\partial E\left(y_i \mid x_i\right)}{\partial x_i} \cdot \frac{x_i}{E\left(y_i \mid x_i\right)} = \beta_i \cdot x_i \tag{C4}$$

The direct point elasticity formula indicates that a one percentage change in the *i*th regressor, *ceteris paribus*, leads to a one percentage change in the rate or expected frequency of $\beta \cdot x_i$. In contrast, where a variable is a dummy variable (1,0), a one percentage change is inappropriate, and a direct arc elasticity form is used as given in equation (C5).

$$\begin{aligned} \text{Arc Elasticity} \Rightarrow & \frac{E\left(y_i \mid x_1\right) - E\left(y_i \mid x_2\right)}{x_1 - x_2} \cdot \frac{\left(x_1 + x_2\right)/2}{\left(E\left(y_i \mid x_1\right) + E\left(y_i \mid x_2\right)\right)/2} \\ & = \frac{E\left(y_i \mid 1\right) - E\left(y_i \mid 0\right)}{E\left(y_i \mid 1\right) + E\left(y_i \mid 0\right)} \end{aligned} \tag{C5}$$

The arc elasticity interpretation is equivalent to the direct elasticity presented in equation (C4) but it has to be multiplied by 100 to represent a 100% change (from 1 to 0, or 0 to 1).

Table C1: Model estimates for respondents currently employed (workers) located in the GSMA – mean (t value)

GSMA workers	Commute	Work-related	Education	Food shopping	General shopping	Personal business	Social recreation	Visit sick/elderly
Constant	2.100 (61.04)	-0.109 (0.48)	-2.024 (7.87)	1.093 (13.70)	0.677 (5.18)	-0.426 (3.21)	0.246 (2.88)	-2.496 (6.09)
Age (years)		-0.007 (1.92)	0.007 (1.67)		-0.006 (2.02)			0.025 (3.75)
Gender female (0,1)	-0.226 (5.11)	-0.466 (4.03)	0.723 (6.82)					0.412 (2.18)
Personal income ('000AUD$)		0.003 (3.88)				0.004 (3.97)	0.003 (4.92)	0.005 (3.65)
Number of children in household			0.713 (18.96)	-0.098 (2.78)		-0.105 (1.66)	-0.113 (2.77)	
Number of cars per adult in household		0.162 (2.15)	0.456 (6.41)	0.117 (2.22)				
Distance from home to office (kms)				-0.004 (2.53)		-0.005 (1.62)		-0.016 (2.74)
Proportion of days WFH	-1.556 (19.33)		0.255 (2.30)			0.282 (1.93)	0.189 (1.91)	
Occupation clerical and administration (0,1)			-0.355 (2.35)				0.227 (2.48)	-0.687 (2.69)
Occupation sales (0,1)				-0.350 (2.88)				-2.724 (3.71)
Occupation blue collar (0,1)		0.480 (3.72)			0.250 (2.40)			
Used car to go to work last week (0,1)		-0.123 (2.10)		-0.075 (2.27)	-0.152 (3.38)	-0.134 (2.14)	0.138 (3.29)	-0.424 (4.12)
Newcastle (0,1)					0.240 (2.48)	0.358 (2.70)		1.411 (7.15)
Factor analysis: authorities and community response				0.067 (2.12)				0.261 (2.40)
Factor analysis: social meetings		-0.201 (4.97)	-0.123 (3.17)		0.119 (2.94)	0.114 (2.05)	0.179 (5.94)	0.183 (2.08)
Factor analysis: all meetings					0.152 (3.60)	0.099 (1.79)		0.529 (5.24)
Factor analysis: concerned about health	-0.129 (2.90)	-0.165 (2.89)						-0.275 (2.04)
Factor analysis: public transport concerned		0.123 (2.09)		0.079 (2.40)	0.152 (3.38)	0.139 (2.21)	-0.139 (3.30)	0.440 (4.25)
Interaction between factor concerned about health and use of car to go to work last week			0.000 (1.98)					
Interaction between factor concerned about health and proportion of days WFH							-0.144 (1.92)	0.669 (3.14)
Restricted log-likelihood	**-1,480.65**	**-747.09**	**-882.70**	**-972.78**	**-776.49**	**-598.61**	**-954.44**	**-428.88**
Log-likelihood at convergence	**-1,202.40**	**-680.28**	**-645.84**	**-954.15**	**-755.91**	**-577.15**	**-901.18**	**-356.08**
AIC/n	**6.20**	**3.54**	**3.36**	**4.93**	**3.92**	**3.01**	**4.67**	**1.90**
Sample size	**390**	**390**	**390**	**390**	**390**	**390**	**390**	**390**

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