Advanced modelling of commuter choice model and work from home during COVID-19 restrictions in Australia

Camila Balbontin
David A. Hensher
Matthew J. Beck
Institute of Transport and Logistics Studies (ITLS)
The University of Sydney Business School
Sydney NSW Australia 2006
Camila.Balbontin@sydney.edu.au
Matthew.Beck@sydney.edu.au
David.Hensher@sydney.edu.au
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Abstract

The decision to work from home (WFH) or to commute during COVID-19 is having a major structural impact on individuals' travel, work and lifestyle. There are many possible factors influencing this non-marginal change, some of which are captured by objective variables while others are best represented by a number of underlying latent traits captured by attitudes towards WFH and the use of specific modes of transport for the commute that have a bio-security risk such as public transport (PT). We develop and implement a hybrid choice model to investigate the sources of influence, accounting for the endogenous nature of latent soft variables for workers in metropolitan areas in New South Wales and Queensland. The data was collected between September-October 2020, during a period of no lockdown and relatively minor restrictions on workplaces and public gatherings. The results show that one of the most important attributes defining the WFH loving attitude is the workplace policy towards WFH, with workers that can decide where to work having a higher probability of WFH, followed by those that are being directed to, relative to other workplace policies. The bio-security concern with using shared modes such as public transport is a key driver of WFH and choosing to commute via the safer environment of the private car.

Key Words: Working from home; hybrid choice model, commuting activity, COVID-19

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1 Introduction

The COVID-19 pandemic has had serious global implications, particularly for health matters, which have resulted in significant changes in the way businesses and people operate on a daily basis. Businesses around the world have adapted quickly to the changing circumstances, allowing their workers to work from home (WFH) when possible – which has had a major influence on not only the nature of where and how work is done, but on the performance of the transport network. During these uncertain times, attitudes, perceptions, and beliefs are likely to be playing, and continue to play, a very important role in individual choice making and behaviour related to working from home and/or commuting, and most notably on the use of shared modes such as public transport (PT).

In this paper, a hybrid choice model will be used to identify the nature and role of underlying attitudes, perceptions and beliefs that influence the decision to work from home for a specified number of days per week, and how this relates to the incidence of commuting by day of the week and time of day. The hybrid choice model is estimated to account for the latent structure associated with a number of important soft variables related to perceived productivity and overall advantages of working from home, and concern towards the use of public transport due to COVID-19. The choice model considers 12 different alternatives for each day of the week: not to work, WFH, and to commute by up to 10 different modes of transport (depending on which modes are available to each individual). The latent variables feed into this model in an endogenous way to understand how the attitude towards WFH and the concern towards PT influence the probability to not work, WFH or commute by a specific mode each day of the week. The data was collected during late 2020 as part of a larger ongoing study to understand the implications of COVID-19 on the transport network around Australia (see Hensher, Beck, et al., 2021a; Beck & Hensher, 2020). Data from workers in two metropolitan areas will be used, the Greater Sydney Metropolitan Area (GSMA) and Southeast Queensland area (SEQ).

This paper is organised as follows. The next section presents a brief background of literature on the impacts of COVID-19 on travel behaviour and how the pandemic has been considered to date within the setting of a hybrid choice model. Section 3 presents the data used in this study. The next section describes the methodology used in this study, followed by the model results and value of travel time savings and elasticities. Section 7 presents simulated scenarios, and the final section discusses the main findings.

2 Literature Review

Hybrid choice models which integrate discrete choice models with latent variables have been developed over a number of years, with early examples by Walker (2001) and Walker & Ben-Akiva (2002), and are reviewed in a number of sources such as Hensher et al. (2015). These models emphasise the importance of amorphous influences on behaviour such as knowledge and attitudes. Several articles have found interesting results when incorporating latent variables, that allow for a better understanding of individuals preferences and how these underlying attitudes affect their choice making (Daly et al., 2012; Prato et al., 2012; Morikawa et al., 2015; Beck & Hess, 2017). COVID-19 as an extreme event has influenced in a significant way how we work, travel and live, resulting in changes that have impacted on the transport systems, notably attributed to working from home and bio-security concerns over using public transport and other shared modes. Our interest in this paper is how we might integrate revealed preference data on actual changes in travel behaviour and the growth in WFH with a number of soft latent variables that represent underlying attitudes and opinions that condition observed travel and non-travel activities. Before presenting new evidence, we review a number of existing studies that are relevant to the focus of this paper and that also used hybrid choice models in this context.

Beck et al. (2021) use data collected across three waves in Australia throughout 2020 to study the impacts of COVID-19 on the number of trips by public transport. They use a zero inflated Poisson regression model to explain the number of trips by public transport by different socioeconomic characteristics and attitudes towards the use of public transport. They incorporate latent variables as explanatory variables in the utility function (estimated through factor analysis). The findings suggest that individuals concerned about public transport before COVID-19 and during the first (March 2020) and second (June 2020) data collection periods, usually make more weekly trips, suggesting that greater exposure is driving the attitudes towards hygiene and risk. Those that are more concerned about the hygiene in public transport tend to have higher odds of making zero public transport trips in the data collected after COVID-19, switching to greater use of the private car.

Balbontin et al. (2021) undertook a similar study using data collected in Australia in late 2020. They incorporate latent variables as additional explanatory variables in a model explaining weekly commuting and non-commuting trips. The results in metropolitan areas suggest that people that love WFH tend to commute more than those that do not love WFH, suggesting that people prefer a balance between WFH and going to the office. In terms of concern towards public transport, these results suggest that public transport commuters also tend to do less work-related travel and fewer social/recreation trips. The focus of this study was understanding the influences on the number of weekly commuting and non-commuting trips, as opposed to the current paper, which focuses on identifying the influences on the daily probability to not work, work from home or commute.

Hurtubia et al. (2021) estimate a hybrid choice model that integrates a discrete choice model with latent variables to identify the probability of working from home versus going to the office. They use data collected in Chile at the beginning of the pandemic, during March 2020 and consider two latent variables: one associated with concern towards health and the other one concern towards the economy. Their results show that female respondents, respondents with a lower income, and older residents, are more concerned about health, which has a positive influence on the probability to WFH, possibly due to greater transmission risk outside the home and the severity of COVID-19 if they catch it. Their results also suggest that respondents with a lower income, without secondary education, or independent workers, are more concerned about the economy, resulting in a negative influence on the probability to WFH.

Aaditya and Rahul (2021) also develop a hybrid choice model to identify the influence of awareness of COVID-19 on the modal shift in India. Their results suggest a significant modal shift from public transport to personal vehicle use, attributed to the increased awareness of COVID-19 and a perception of the deterioration in public transport safety. Their findings suggest that respondents were willing to reconsider using public transport in a post-lockdown scenario if several preventive measures towards COVID-19 were implemented (e.g., social distancing, crowd management, and sanitisation).

Hensher et al. (2022), developed a model system to identify the choice between working from home as opposed to commuting and not working by day of the week and time of day in Australia. They estimated a mixed multinomial logit model to determine and map the probability to WFH using individuals' socioeconomic characteristics, modal attributes such as time and cost, day of week and time of day and some attitudinal variables such as concern about using public transport. The model outputs provide evidence of the key drivers of the probability of WFH compared to commuting over a week and form the basis of a mapping equation in the construction of a full origin-destination (OD) matrix for the study area to identify the varying spatial incidence of WFH across the OD pairs.

Since the start of COVID-19 in March 2020, there has been an accumulating body of research undertaken to gain an understanding of the impact that the pandemic has had on some major consequences, notably WFH and reduced use of public transport. These studies have identified a range of key influences, both of a quantitative nature such as socioeconomic descriptors, but also of a qualitative nature such as attitudes and opinions. These latter latent variables require an endogenous treatment when mixed with the other explanatory variables, resulting in a preference for a hybrid choice model. To the best of our knowledge, there are no current studies that have investigated attitudes towards public transport and work from home in the context of daily mode choice into a hybrid choice model, including not to work and work from home as possible alternatives. In this paper we focus on gaining a greater understanding on how attitudes towards work from home and concerns about COVID-19 are influencing individuals' decision not to work, to work from home or to commute by different modes of transport.

3 Data Description

The data was collected during late 2020 as part of a larger ongoing study to understand the implications of COVID-19 on the transport network around Australia (Beck & Hensher, 2020; Hensher, Beck, et al., 2021b). Data from two metropolitan areas will be used in this paper, the Greater Sydney Metropolitan Area (GSMA) comprising the Sydney Metropolitan Area, Newcastle and the Illawarra/Wollongong, and Southeast Queensland area (SEQ), the latter comprising the Sunshine Coast, Brisbane metropolitan area and the Gold Coast. During the time period being analysed, Australia had pursued an elimination strategy with relative success, having emerged from lockdown in June 2021 and (outside of Victoria) having had a sustained period of zero community transmission, with COVID-19 cases in the GSMA and SEQ being almost exclusively within the hotel quarantine system. As such, in October 2020 both metropolitan areas had returned to minimal government-imposed restrictions on travel, activities, and work.

Respondents answered questions about work behaviour prior to COVID-19, for example: which days they worked (Monday, Tuesday, etc., including weekends), where did they do work each day, and the modes of transport available to them for commuting and non-commuting. A number of attitudinal statements were included, with a specific focus on attitudes towards WFH and public transport use (PT), which will be used as indicators in the hybrid choice model. 650 respondents completed the survey, indicating where they worked from each day of the week so, in total, we have 4,518 observations for modelling[1]. An overview of the sample is presented in Table 1. 63% of respondents are located in the GSMA and the rest in SEQ. 39% of respondents have their own place or room to WFH. In terms of WFH, prior to COVID-19, on average, respondents worked 0.86 days from home, while they worked on average 1.64 days last week (i.e., at the time of the survey). The total number of days worked is relatively similar, with an average of 4.59 days worked prior to COVID-19 and 4.51 last week.

Table 1: General sample characteristics

Variable	Mean (std deviation)
Age (years old)	40.10 (13.40)
Gender female (1,0)	0.64
Income ('00AUD$) personal	78.13 (51.81)
Number of adults in household	2.79 (1.32)
Number of cars per adult in household	0.65 (0.36)
Occupation labour and machine operators (1,0)	0.06

[1] Some respondents did not provide the correct information for all the days of the week which had to be excluded.

Variable	Mean (std deviation)
Occupation white collar (1,0)	0.84
Workplace located in CBD (1,0)	0.21
Has their own space to WFH (1,0)	0.39
Located in the GSMA in New South Wales (1,0)	0.63
Located in Brisbane (1,0)	0.21
Located in the Sunshine Coast (1,0)	0.05 (0.22)
Number of days WFH last week	1.64 (2.11)
Number of days worked last week	4.51 (1.28)
Number of days WFH prior to COVID-19	0.86 (1.60)
Number of days worked last week prior to COVID-19	4.59 (1.06)
Sample size	**650**

For those respondents who made a commuting trip(s) over the last week, the trip characteristics reported are presented in Table 2. The majority of respondents (68%) used a private car to go to work last week (prior to COVID-19 it was 62%), while 12% used active modes (walk, bicycle including e-scooters) (prior to COVID-19 it was 8%). The average travel time by active modes is of 33.3 minutes, the average in-vehicle time in public transport is 32.9 minutes, taxi/rideshare averages 25.2 minutes, and in private motorised vehicles, the average time is 28.6 minutes.

Table 2: Commuting trip characteristics

Variable	Mean (std deviation)
Used car to go to work last week (1,0)	0.68
Used public transport to go to work last week (0,1)	0.19
Used bicycle or walked to work last week (1,0)	0.12
Used car to go to work last week (1,0)	0.62
Used public transport to go to work prior to COVID-19 (0,1)	0.29
Used bicycle or walked to work last week (1,0)	0.08
Walking or bicycle available to go to work (1,0)	0.31
Public transport available to go to work (1,0)	0.66
Rideshare/taxi available to go to work (1,0)	0.32
Car driver, passenger or motorcycle available to go to work (1,0)	0.83
Walking or bicycle travel time (minutes)	33.31 (27.63)
Public transport in-vehicle travel time (minutes)	32.86 (23.97)
Rideshare/taxi travel time (minutes)	25.15 (22.26)
Car driver, passenger or motorcycle travel time (minutes)	28.64 (30.96)
Public transport fare (AUD$)	6.83 (8.91)
Rideshare/taxi fare (AUD$)	39.05 (56.33)
Car driver, passenger or motorcycle cost (AUD$)	6.22 (15.35)
Public transport access, egress and waiting time (minutes)	42.89 (33.02)

Figure 1 summarises the work from home policy of participants' place of employment at the time of the survey, i.e., end of 2020[2]. Over 30% of respondents said their place of employment did not have plans to allow them to WFH, 29% of respondents said they were given the choice to WFH when they chose to, 21% of respondents said it is not possible for them to WFH as they need to be onsite to do their job, and over 19% of respondents said their place of employment is directing them to WFH.

[2] Note that, while no longer in place, during the early part of the year when more stringent health orders were in force, workplaces were required to allow staff to work from home if it was reasonably practicable to do so.

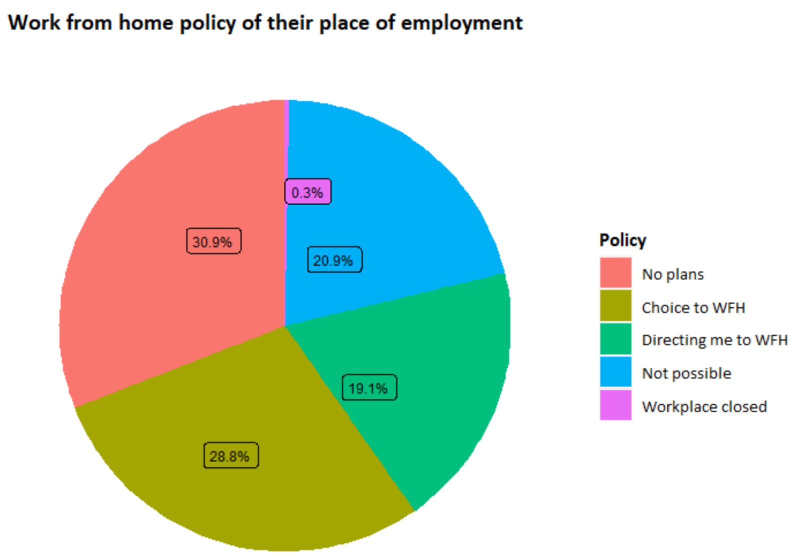

Figure 1: Work from home policy of their place of employment as it stands today

Figure 2 presents the commuting, work from home and not work partition in the sample, by day of week. Work from home is relatively stable across weekdays, varying between 35% and 39%. The variation in behaviour is observed mainly in commuting and not working on any given day, perhaps indicating that those who are required to travel to work are working less days per week compared to those who are able to work from home.. On Fridays, the percentage of participants not working is the highest across weekdays, where 26% of participants reported not working; the lowest is on Wednesdays where less than 15% of participants reported not working. On weekends, the majority of participants do not work (almost 84% Saturday and over 90% on Sunday), but the existence of a reasonable amount of weekend work means that all seven days should be included in the analysis in WFH opens up greater flexibility for many workers as to when work is undertaken. There seem to be some (see Hensher et al., 2022 and Beck & Hensher, 2020) differences across days of the week, although the main change is between weekdays and weekends, as expected.

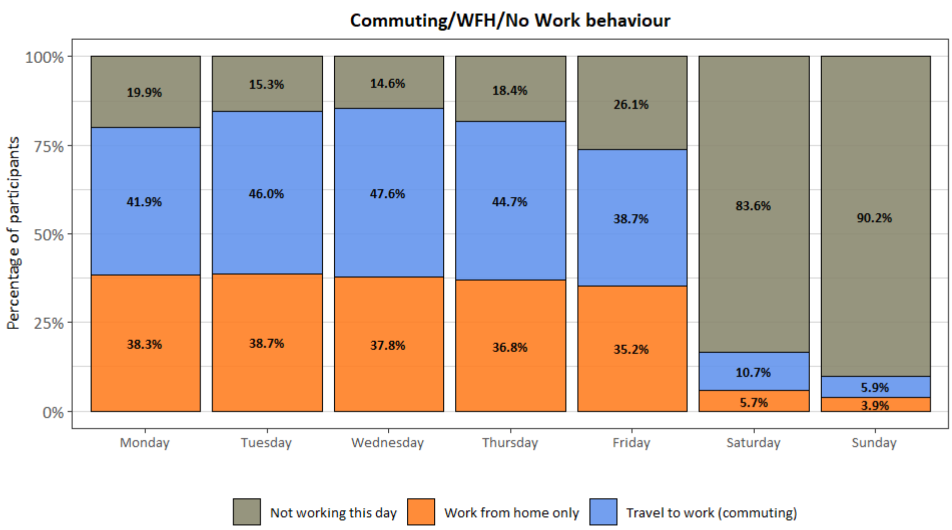

Figure 2: Commuting, WFH and no work behaviour

Figure 3 summarises the overall modal share prior to COVID-19 compared to the situation at the time of the survey. Results show a significant increase in the use of motorised private vehicles (car driver, passenger and motorcycle), with a particular increase in car driver, as is expected given the health concerns associated with shared modes. The results indicate a significant decrease in the use of train from almost 19% to slightly more than 12%; and in the use of bus from almost 10% to almost 7% of participants. The modal share of light rail and ferry is not significant compared to the other two modes of public transport: bus and train. In terms of active transport, results show an increase from 5.9 to 9.7% in walking, whereas the use of bicycle has remained almost the same.

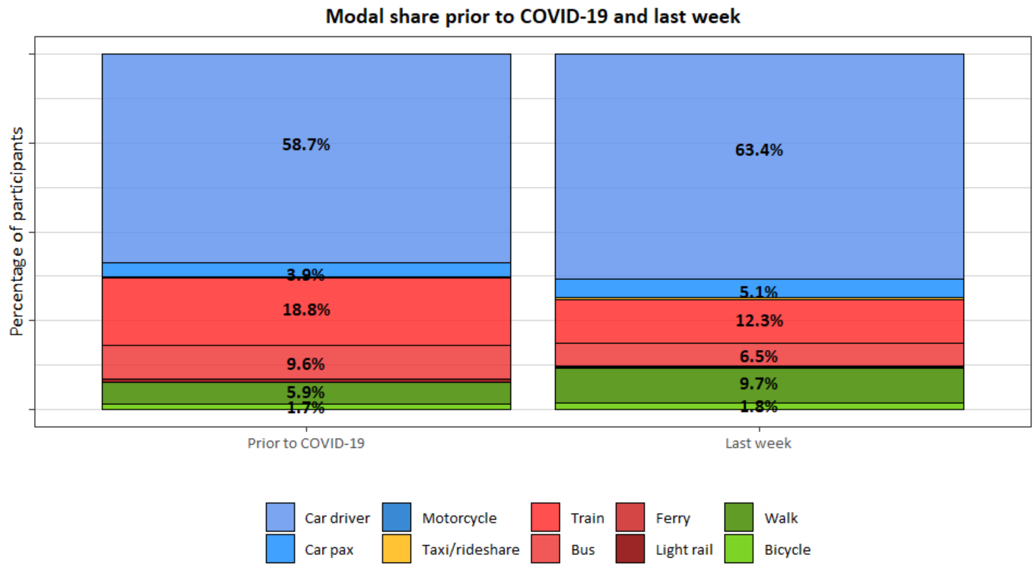

Figure 3: Modal share prior to COVID-19 and currently

A particularly interesting finding related to the modal services is shown in Figure 4, summarising the sample's experience when waiting for public transport. Around 33% of participants do not have public transport available to go to work (which is accounted for when modelling mode choice), so they did not answer this question; approximately 59% of participants said they entered a PT mode when they wanted to without delay, while 7% said they had to wait longer than normal, and less than 1% said they had to wait so long that they gave up using PT. In this study, we are interested in understanding if the experience in waiting for PT, which is related to crowding and frequency, has any impact on participants' concern towards using public transport.

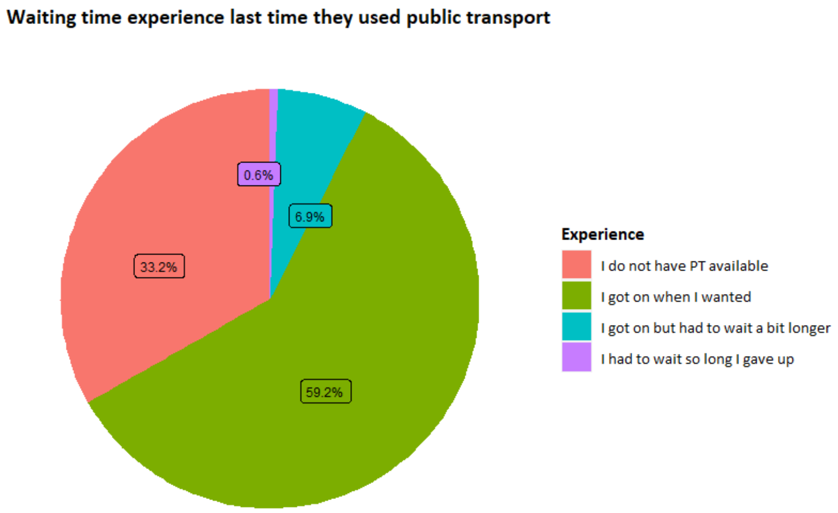

Figure 4: Waiting time experience last time they used public transport

4 The Model Framework

The hybrid choice model structure considers three alternatives for each day of the week: not work, work from home, or work outside home. If someone decided to work outside home, the mode used is relevant in understanding individual commuting behaviour. The daily alternatives' structure is presented in Figure 5.

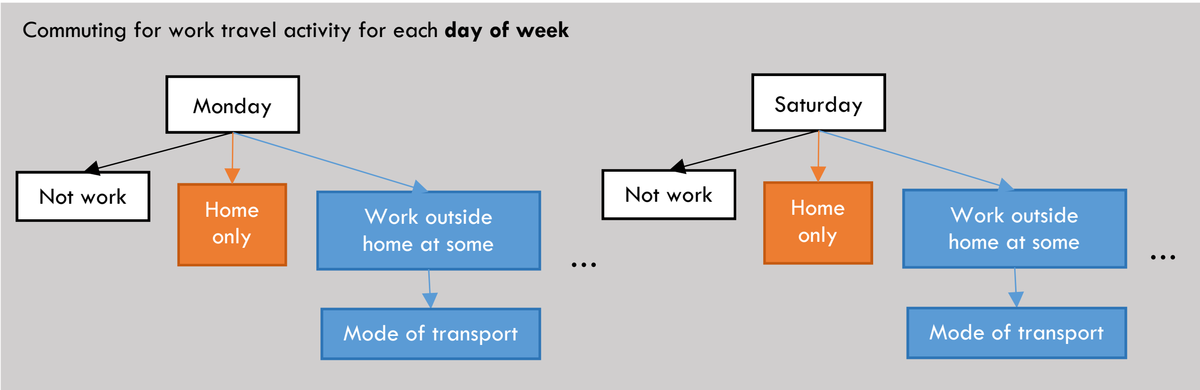

Figure 5: Individuals' daily alternatives structure

For each day of the week, respondents can have up to 12 alternatives available, which are presented in Table 3. The alternatives available will depend on which modes of transport are available to the respondent for commuting, and if they can work from home.

Table 3: Alternative numbers per DoW

	Monday - Sunday
Altij	**Description**
1	Not work
2	Work from home only
3	Work outside home - car driver
4	Work outside home - car passenger
5	Work outside home - taxi/rideshare
6	Work outside home - train
7	Work outside home - bus
8	Work outside home - light rail
9	Work outside home - ferry
10	Work outside home - walk
11	Work outside home - bicycle
12	Work outside home - motorcycle

The overall modelling framework is presented in Figure 6. The proposed model accounts for preference heterogeneity through random parameters (error components) and allows for the panel effect across the observations related to the same individual for different days of the week.

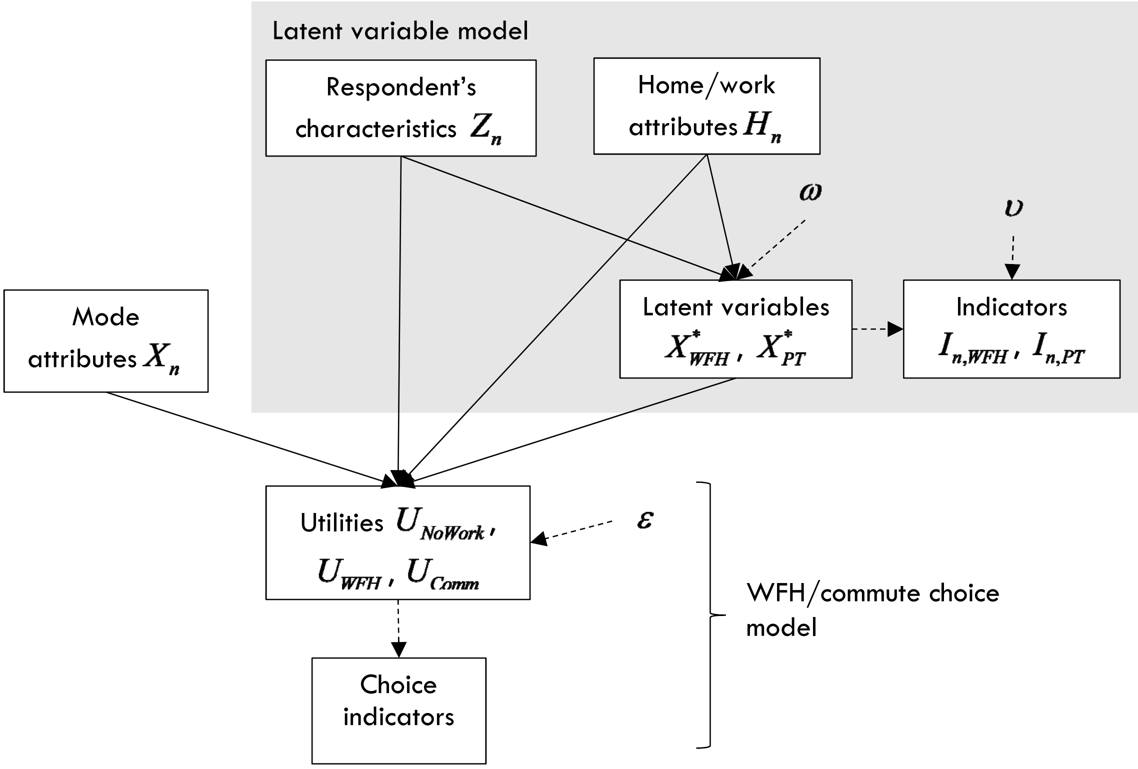

Figure 6: Hybrid model framework

The latent variables refer to variables that cannot be directly observed but are explained by certain indicators. Two latent variables will be considered: (1) WFH lovers, X^*_{WFH} and (2) Individuals concerned about using public transport (PT) to go to workplace due to COVID-19, X^*_{PT}. The linear structural equations of the latent variables are expressed as follows:

$$X^*_{WFH} = \sum_j \theta_j \cdot Z_{qj} + \sum_i \theta_i \cdot H_{qi} + \omega_{WFH} + \eta_{WFH}$$

$$X^*_{PT} = \sum_j \theta_j \cdot Z_{qj} + \sum_i \theta_i \cdot H_{qi} + \omega_{PT} + \eta_{PT} \tag{1}$$

where Z_{qj} represents attribute *j* of respondent *q* (e.g., age, income); H_{ni} represents attribute *i* of the home or work of respondent *q* (e.g., distance to work); θ are the estimated parameters associated with each attribute; ω_n are the error terms associated to the latent variable *n;* and η_n is a part of the error term that takes into account the relationship between the structural equations and the choice model derived from using simultaneous estimation of the hybrid choice model, referred to as serial correlation. The error terms ω and η are normally distributed with a mean of 0 and a standard deviation equal to 1.

The measurement equations of the latent variables are linear additive, as follows:

$$I_n = \alpha_1 \cdot X^*_n + \upsilon_n \tag{2}$$

where I_n represents an indicator associated with the latent variable X^*_n; α are the parameters to be estimated; and υ_n the error term. The indicators are attitudinal questions asked in the survey, as shown in Table 4 and Table 5.

Table 4: Indicators associated with the latent variable WFH lovers

Acronym	Question
WFHPrdM	How productive do you think you have been in the last week whilst working from home?*
BalPdUnP	I am able to find a balance between paid work and unpaid work (e.g., housework, yard work, childcare)**
ReqEqu	I still require equipment / technology to be able to complete work from home as well as I would like**
WFHlFlex	I would like to have more flexible starting and finishing times in the future**

*Scale: A lot less productive (1), A little less productive (2), About the same (3), A little more productive (4), A lot more productive (5)
**Scale: Strongly disagree or disagree (1), Somewhat disagree (2), Neither agree nor disagree (3), Somewhat agree (4), Agree or strongly agree (5)

Table 5: Indicators associated with the latent variable concerned about PT and workplace*

Acronym	Question
ACvConc	Imagine you had to catch public transport tomorrow, what would be your level of concern about hygiene be?
ACvCoNUs	Imagine you had to catch public transport tomorrow, what would be your level of concern about the number of people using public transport?
WkEnvCnc	How concerned are you today about Covid-19 and work, given the environment that you normally work in (i.e., before Covid-19)?

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

These indicators were measured on a Likert scale with 5 levels and for model estimation we define four parameters, τ_i. We assumed symmetry in the indicators, using two positive parameters as follows:

$$\begin{aligned} \tau_1 &= -\delta_1 - \delta_2 \\ \tau_2 &= -\delta_1 \\ \tau_3 &= \delta_1 \\ \tau_4 &= \delta_1 + \delta_2 \end{aligned} \tag{3}$$

The probability of a given response is given by an ordered probit model (Greene & Hensher, 2010). The latent variable that represents attitudes towards WFH will be included in the utility function of the WFH alternative, which can be expressed as follows:

$$U_{WFH} = \beta_0 + \sum_j \beta_j \cdot Z_{qj} + \sum_i \beta_i \cdot H_{qi} + \beta_{WFH} \cdot X^*_{WFH} + \varepsilon_{WFH} + \eta_{WFH} \tag{4}$$

The latent variable that represents concern towards the use of public transport is included in the commuting alternatives, as follows:

$$U_{Commute_m} = \beta_0 + \sum_j \beta_j \cdot Z_{qj} + \sum_i \beta_i \cdot H_{qi} + \sum_k \beta_k \cdot X_{mk} + \beta_{PTm} \cdot X^*_{PT} + \varepsilon_{Commute_m} + \eta_{PT} \tag{5}$$

The utility function of the no work alternative is expressed equation (6).:

$$U_{NoWork} = \beta_0 + \sum_j \beta_j \cdot Z_{qj} + \varepsilon_{NoWork} \tag{6}$$

It is important to note that the error term associated with the WFH alternative, ε_{WFH}, is different to the error term associated with the WFH latent variable structural equation, η_{WFH}. Similarly, with the error term associated with the alternative to commute by mode *m*, $\varepsilon_{Commute_m}$, and the error term associated with the PT concern latent variable structural equation, η_{PT}. Respondents provided responses on the choice made each day of the week, and hence there are 7 choice sets per respondent. To recognise this, the error terms account for the panel structure of the data, i.e., varying across individuals but the same within individuals. The hybrid model was estimated simultaneously using the Apollo Software (Hess & Palma, 2019).

5 Results

The final model includes the structural equations for the WFH and PT variables, as well as the choice model between the alternatives of no work, WFH, and commute by each mode. All the parameter estimates in the final model are statistically significant at a 90% confidence level, with the majority being so at the 95% confidence level.

5.1 Structural Equations

The model results for the structural equations for the WFH lover and PT concern latent variables are presented in Table 6 and Table 7, respectively. The results show that respondents between 25 and 40 years old are the ones that feel more positive towards WFH, followed by those older than 40 years. Our broader research on WFH (Beck and Hensher 2021) suggest that younger employees are keener to return to the office for a number of reasons including social interaction and building networks for career progression. Respondents with a personal annual income above AUD$200,000 tend to be less positive towards WFH, as well as people that work as labourers. There are only a few respondents in the sample with an income level over AUD$200,000, and most of them are either managers or employers, who might be more inclined to attend the office perhaps preferring to manage people in a non-remote environment[3]. If the respondent has their own space or room to WFH, they are more positive towards doing so. There are some location-specific dummy variables that were statistically significant in the WFH lover latent variable, which shows that respondents whose work is located in the Sunshine Coast are more positive towards WFH, followed by those who work in Brisbane, relative to the rest of the study locations (including the GSMA). The workplace attitudes towards WFH have a statistically significant influence on the attitude towards WFH, showing that people that are being directed to work from home or are given the choice to do so, are more positive towards WFH than those who are not.

The structural equation results representing the level of concern towards the use of public transport (PT) show that those respondents in white collar occupations tend to be more concerned about PT, possibly because they tended to use PT more pre-COVID-19 than blue collar workers[4]. People that used the car to commute to work in the last week are the most concerned about the use of PT, somehow explaining the amount of PT users prior to COVID-19 who are now driving, followed by those that used active modes to go to work last week. Respondents that work in central business districts (CBD) areas tend to feel more concerned about the use of PT (because they are mainly office workers travelling in relatively high-density PT settings pre-COVID-19), followed by those who work in the GSMA in NSW, relative to the rest of the study locations (including SEQ in QLD). Results suggest that people that could board the bus/train/light rail without delay in waiting are less concerned about the use of PT than those that had to queue longer than prior to COVID-19, presumably linked to crowding and its associated transmission risk.

[3] https://hbr.org/2020/07/remote-managers-are-having-trust-issues

[4] In our sample, 30% of white-collar workers used public transport prior to COVID-19, as opposed to 22% of blue-collar workers.

Table 6: Structural equation model estimates for WFH lover latent variable

Description	Mean	T-Value
Intercept	0.790	0.459
Personal income above AUD$200,000 (1,0)	-4.835	-2.002
Age between 25 and 40 years old (1,0)	2.324	2.114
Age older than 40 years old (1,0)	2.046	1.874
Has own space or room to work from home (1,0)	2.018	2.789
Occupation labourer (1,0)	-4.080	-1.981
Workplace located in Brisbane (1,0)	2.188	2.261
Workplace located in Sunshine Coast (1,0)	2.875	1.874
My workplace is directing me to work from home (1,0)	6.785	4.090
My workplace gives me the choice to work from home (1,0)	4.384	3.753

Table 7: Structural equation model estimates for PT concern latent variable

Description	Mean	T-Value
Intercept	-0.704	-3.231
Occupation white collar (1,0)	0.542	3.670
Workplace located in CBD (1,0)	0.343	2.262
Workplace located in New South Wales (1,0)	0.435	3.771
Last week used car to go to work (1,0)	1.020	6.314
Last week used bicycle or walked to go to work (1,0)	0.667	2.924
Last time I used public transport I got on when I wanted (1,0)	-0.305	-2.457

5.2 Choice Model

The choice model parameter estimates are presented in Table 8, together with the results of a stand-alone mixed logit model (MML). This MML model includes an error component in the no work and the commuting alternatives that takes into account the panel nature of the data, which is normally distributed with mean 0 and an estimated standard deviation, equivalent to the hybrid choice model. The overall goodness of fit of the choice model component of the hybrid model[5] is statistically superior to the MML model, reinforcing the position that taking into account respondents' underlying attitudes towards WFH and the concern towards the use of PT as latent variables significantly improves the statistical fit of the model and provides an improved understanding of individual preferences.

The results suggest that female respondents are more likely to not work any given day. If the respondent has a higher personal income, then they are more likely to WFH, same if they live in a household with more people, if they have more cars per person in their household or if their occupation is clerical and administration. Similarly, if they work in the Central Business District (CBD), and/or in the GSMA of NSW they are more likely to WFH. This is reinforced by evidence in Hensher et al. (2022) where SEQ displays a lower incidence of WFH than the GSMA. In terms of the days, respondents seem more likely to WFH on Mondays, followed by Tuesday, then Wednesday, Thursday and Friday, relative to weekends. As expected, the travel time, access, egress and waiting time and cost have a negative marginal utility influence in the choosing of a specific mode of transport, with separate parameter estimates for motorised and non-motorised (i.e., walk and bicycle) modes.

The WFH lover latent variable has a positive influence on the probability to WFH, while the level of concern towards public transport has a negative influence on the probability to commute by train, followed by light rail and bus, relative to the other modes of transport.

[5] The log-likelihood of the full hybrid model takes into account the estimation of the ordered probit model of the latent variables, and of the mixed logit model of the choice model. The log-likelihood of the second model of the hybrid choice model is calculated to be able to compare it with a simple MML model.

Table 8: Choice model parameter estimates

Description	Alternative	MML	Hybrid model
Alternative specific constant no work (base)	No Work	-	-
Alternative specific constant WFH	WFH	-2.53 (10.29)	-7.34 (9.08)
Alternative specific constant commute by car driver	Car driver	0.18 (1.47)	0.17 (1.20)
Alternative specific constant commute by car pax	Car pax	-1.37 (10.78)	-1.39 (10.31)
Alternative specific constant commute by taxi/rideshare	Taxi/Rideshare	-3.07 (9.01)	-3.14 (9.11)
Alternative specific constant commute by train	Train	-2.56 (8.14)	-1.73 (6.25)
Alternative specific constant commute by bus	Bus	-3.03 (9.61)	-2.29 (8.30)
Alternative specific constant commute by light rail	Light rail	-2.74 (6.07)	-1.89 (4.53)
Alternative specific constant commute by ferry	Ferry	-3.76 (5.30)	-2.89 (3.98)
Alternative specific constant commute walking	Walking	-0.16 (0.81)	-0.26 (1.27)
Alternative specific constant commute by bicycle	Bicycle	-1.16 (4.96)	-1.16 (4.82)
Alternative specific constant commute by motorcycle	Motorcycle	-1.22 (4.39)	-1.22 (4.31)
In-vehicle travel time (mins)	All motorised modes	-0.003 (1.80)	-0.003 (1.92)
Travel time active modes (mins)	Walking and bicycle	-0.02 (5.45)	-0.02 (5.21)
Access, egress and waiting time (mins)	Train, Bus, Light Rail and Ferry	-0.01 (2.40)	-0.01 (2.31)
Cost (AUD$)	All modes except walking and bicycle	-0.02 (4.93)	-0.02 (4.53)
Female (1,0)	No Work	0.27 (3.12)	0.29 (2.93)
Personal income (‘000$AUD)	WFH	0.00 (3.80)	0.01 (2.57)
Number of individuals per household	WFH	0.11 (2.70)	0.14 (1.84)
Number of cars per person in household	WFH	0.45 (3.48)	0.47 (3.32)
Monday (1,0)	WFH	3.26 (17.17)	4.40 (17.89)
Tuesday (1,0)	WFH	3.15 (16.68)	4.22 (17.43)
Wednesday (1,0)	WFH	3.01 (16.02)	4.02 (16.84)
Thursday (1,0)	WFH	3.00 (16.00)	4.00 (16.79)
Friday (1,0)	WFH	2.95 (15.77)	3.92 (16.59)
Workplace located in CBD (1,0)	WFH	0.48 (3.76)	0.25 (1.07)
Workplace located in New South Wales (1,0)	WFH	0.06 (0.49)	0.76 (2.44)
Latent variable PT concern	Train	-	-0.69 (5.48)
Latent variable PT concern	Bus	-	-0.54 (4.39)
Latent variable PT concern	Light rail	-	-0.68 (2.23)
Latent variable WFH lovers	WFH	-	0.36 (4.26)
Standard deviation error component	No Work	2.53 (10.80)	1.73 (8.70)
Standard deviation error component	Commuting	0.52 (8.67)	0.63 (9.48)
Sample size		***650 respondents and 4,518 observations***	
Choice model			
Number of parameters		***29***	***32***
Log-likelihood		***-4509.91***	***-4,326.63***
AIC/n		***2.009***	***1.929***
Hybrid model (full)			
Number of parameters		***-***	***70***
Log-likelihood		***-***	***-8,536.71***
AIC/n		***-***	***3.810***

6 Elasticities

The sensitivity of the probability to WFH or to commute to changes in the attributes can be analysed through the elasticities, summarised in Figure 7 (numbers are presented in Table 10 in the Appendix), which are the preferred indicators of the nature and extent of behavioural response of most interest. In terms of WFH, results show that a person that has their own space to WFH, *ceteris paribus*, is 13.5% more likely to do so than a person that has to share a space or does not have such space at all. The workplace policy towards WFH is logically a very relevant influence, incorporated through the WFH loving latent variable. It suggests, *ceteris paribus*, that people directed to WFH are 18.0% more likely to do so, while respondents that are given the choice to WFH are 26.5% more likely to do so, relative to other respondents. Since this influence is through the WFH loving attitude, these results are showing that people that are given the choice to WFH have a more positive attitude towards WFH, followed by those that are being directed to WFH. This is an interesting finding. Given that respondents who are able to choose when to work from home and when not to, thus presumably having flexibility to work between home and the regular work environment, are more positive than those who are being directed to WFH and thus presumably must only work from home, we hypothesis that a balance between WFH and going to the office leads to better WFH experiences.

Specifically for public transport, a person that does not have to queue when waiting for their bus, linked we suggest to exposure to others, *ceteris paribus*, is 9.6% more likely to use the bus than a person who has to wait longer than they did prior to COVID-19; and 12.2% more likely in the case of train and light rail. Mask wearing is mandated on-board PT but not at the stops and station, so the health concerns in the stops and stations might be higher than inside the vehicles. The higher influence associated with train and light rail probably could be related to the fact that if there are more people waiting, the vehicles will be more crowded – and considering the train and light rail have a higher capacity of compartments relative to buses, the biosecurity risk associated with them might be higher.

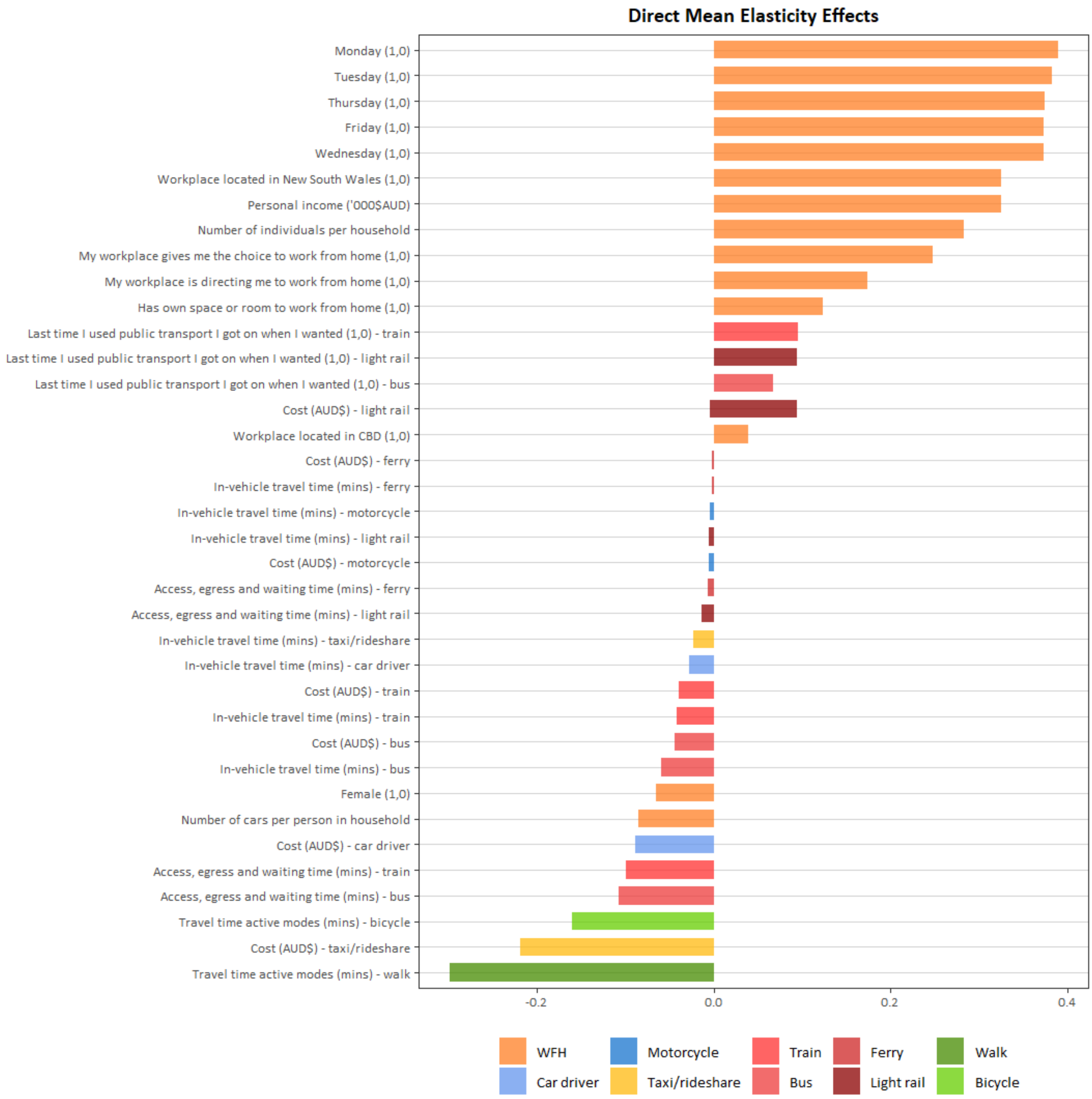

Figure 7: Direct Mean Elasticity Effects Hybrid Choice Model

7 Probability of Working from Home Simulated Scenarios

Five scenarios were simulated to show the sensitivity of the probability to WFH variable due to variations in the explanatory variables. The observed versus estimated results for the hybrid model probability to WFH are presented in Figure 8. The observed probabilities to WFH are lower than the estimated ones using the hybrid model, and they decrease from Monday to Friday. That is, the probability to WFH on Monday is higher than on Tuesday, and so on. The probability to WFH on weekends is much lower which, as was presented in Figure 2, is due to a high proportion of people not working on weekends. These probabilities are the base scenarios, and the simulations represent variations in these base scenarios due to changes in the explanatory variables, which are described in Table 9 with the results presented in Figure 9.

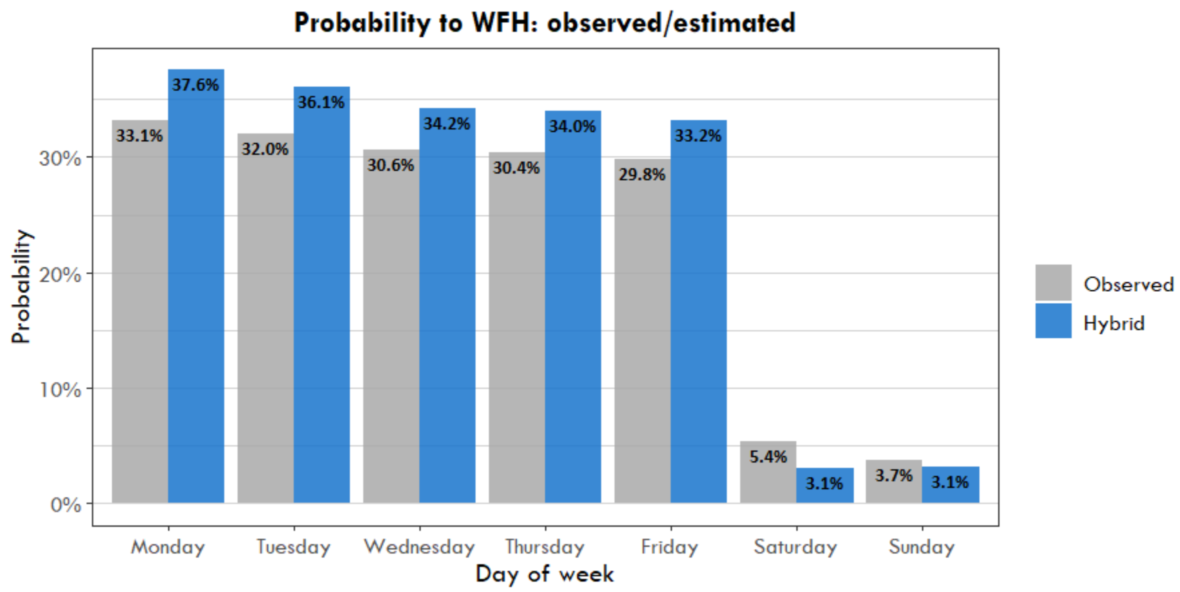

Figure 8: Observed versus estimated probability to WFH

Table 9: Simulated scenarios description

Scenarios	**Description**
1	Everyone has their own space or room to work from home
2	Everyone is a blue-collar worker
4	Everyone has an income level above AUD$200,000 with a population average of AUD$201,000
4	Everyone works in the CBD
5	Travel time in all modes of transport increases by 50%

The first scenario represents a situation where everyone has their own space or room to work from home which currently is 39% (Table 1), which would generate an increase between 1.4% and 1.6% in the probability to WFH on weekdays and 0.4% on weekends. Scenarios 2 to 4 represent subgroups of the population and their behaviour towards WFH. Scenario 3 represents a situation where everyone was a blue-collar worker (i.e., technicians and trades, machine operators/drivers and labourer) where the probability to WFH would decrease between 13.6% and 14.3% on weekdays and 2.3% on weekends. If everyone in the sample would have a high income of above $200,000 with a population average of $201,000 then this would represent a decrease in the probability to WFH between 8.9% and 10.0% on weekdays, and 2.0% on weekends. A high income of above $200,000 has a negative influence in the latent variable WFH lover (which has a positive impact in the probability to WFH), but a higher income has a positive influence in the probability to WFH. This shows that a higher income implies a higher probability to WFH, unless the income is very high (above $200,000), in which case individuals seem to be less positive towards WFH. As previously discussed, this might be due to the fact that only a few individuals in the sample have a very high income (above $200,000) and most of them are managers or employers, who in turn may still prefer to manage or supervise staff in a more traditional framework for reasons of trust and authority, but also that managing during the pandemic has its own set of challenges that may create greater burden (Teodorovicz et al., 2021). Scenario 4 represents the population that works in the CBD area, which has a positive influence in the PT concern latent variable (which has a negative impact in commuting by PT), and also a positive influence in the probability to WFH. The results suggest that if everyone worked in the CBD area, then there would be between a 1.8 to 1.9% increase in the probability to WFH on weekdays and 0.4% on weekends.

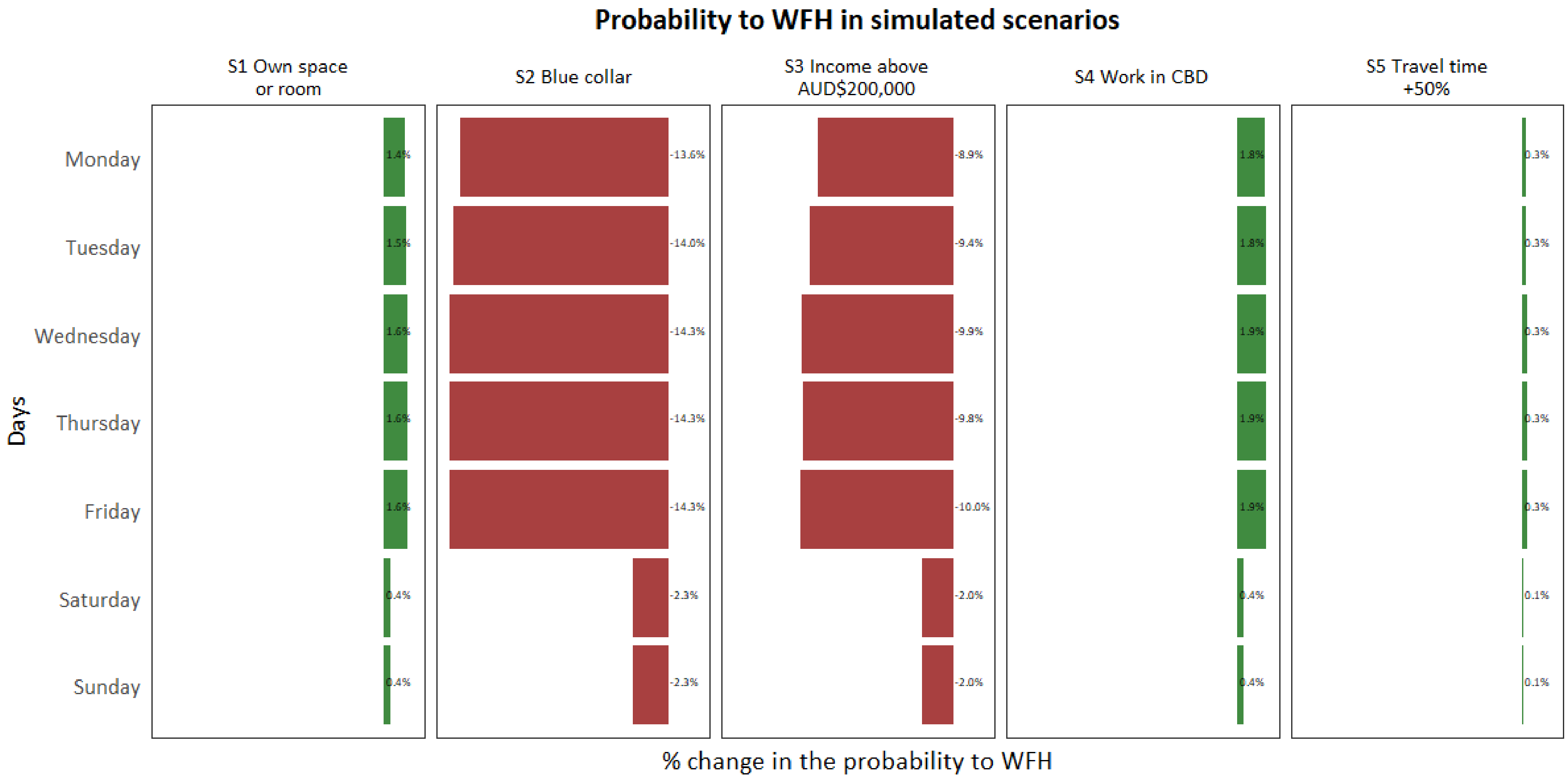

Figure 9: Simulated scenarios results

The last scenario shows the situation where all travel times increase by 50%, which would imply an increase of 0.3% in the probability to WFH on weekdays and 0.1% on weekends. This last scenario is interesting as it shows that travel times are not the most important factors when deciding to WFH (as shown also in Hensher et al., 2022), compared to having their own space to work from home, workplace attitudes towards WFH or even having to wait longer than prior to COVID-19 when waiting for the bus or train/light rail.

8 Conclusions

The main focus of this study is to understand the influence of underlying attitudes towards COVID-19, namely in relation to WFH and the use of PT, in the probability to WFH, to commute or not to work for each day of the week. A hybrid choice model was developed and estimated, integrating a choice model with two latent variables; - WFH loving attitude and PT concerned attitude. The WFH loving attitude has a positive influence on the probability to WFH. Results show that having a very high income (over $200,000 p.a.) has a negative influence on the WFH loving attitude, although income has a positive influence on the probability to WFH. Respondents between 25 and 40 years old are more positive towards WFH, followed by people older than 40 years old. Respondents tend to be more positive towards WFH if they have their own space/office to WFH, if their workplace allows them to decide when to WFH, or if they are directing them to WFH.

The PT concern latent variable had a negative influence on the train, followed by light rail, and followed by bus, relative to all the other alternatives. Results show that respondents that work in white collar occupations are usually more concerned about the use of PT, as are people that work in the city centre (CBD). Respondents that used car to go to work the week prior to the survey tend to be more concerned about PT, followed by respondents that used active modes, relative to other modes of transport. Finally, results show that people that boarded a bus or train when they wanted and did not have to queue longer than prior to COVID-19, tend to be less concerned about the use of PT. These findings have a great deal of plausibility, but what is especially relevant is that we have a series of behaviourally informative model outputs that can be used to provide useful advice into the policy debate on what WFH and resistance to using PT means in respect of changing levels of commuting activity by specific modes. In related research (Hensher, Wei, et al., 2021) we have shown how predictions of WFH by origin-destination pair can be used to adjust the traffic levels on the road network.

The value of travel time savings obtained from the hybrid model was statistically equivalent to the one derived from a mixed multinomial logit model. However, the elasticities obtained from the hybrid choice model provides a much deeper understanding into how different variables are playing a role in the choice to WFH or commute by different modes of transport. The elasticities were calculated using the hybrid choice model results to analyse the sensitivity in the probability to WFH or to commute given changes in the explanatory variables. The results show that people that are being directed to WFH are 18.0% more likely to do so, while respondents that are given the choice to WFH are 26.5% more likely to do so, relative to the other respondents. These results suggests that respondents seem to prefer a balance in WFH, rather than being directed to do so, and that the WFH policies and workspace facilities linked to productivity are one of the most influential factors in the probability to WFH. These are structural issues that are difficult for transport policy makers to directly influence. It seems like a hybrid work model, as opposed to working entirely from the office or from home, will make people more productive and satisfied, obtaining the best of both worlds. To that end, the mechanism for transport policy makers is not only to think of the provision of transport, but how can investment in good technology be seen as a transport investment (i.e., in a new WFH future ICT like the NBN is now also a transport investment). These changes suggest a greater need to work with businesses to encourage sophisticated distribution of WFH so that pressure on the transport network can be relieved intelligently, i.e., potentially a more coordinated approach where business in particularly congested zone (e.g., CBD) have a greater understanding of aggregate travel patterns, spreading WFH over the week and over the day as an area workplace policy.

The model also shows that having an appropriate space to work from home is an important element to the WFH Lover latent construct. In the longer term, should a greater extent of working from home be adopted as we expect it to be, this may place some pressures on both residential design and choices. Those who are working from home more than before COVID-19 might be inclined to seek residential spaces that support this behaviour. In Australia there has been mainstream media reports of increased interest regional homes, but with the hybrid model of work likely to be the one adopted by the majority of workplaces, this might place a natural limit on the distance away from the office people can move (combined with the inherent social and cultural amenity of living near metropolitan regions). Thus, we could potentially see a greater level of suburbanisation rather than regionalisation, driven by workers looking for a better work from home space. Urban building design may have to adapt; including strategies such as apartment complexes including office space within the building for residents (akin to gyms), or even “office space as a service” providers looking to establish themselves. These longer-term implications of working from home will need to be carefully examined.

The elasticities’ results showed that people that did not have to queue were 12.2% more likely to use train and light rail, and 9.6% more likely to use the bus, compared to those that had to queue before getting on the bus or train. This highlights the bio-security risk associated with COVID-19 where mask-wearing and social distance was enforced on public transport but not so waiting for public transport.

Five different scenarios were simulated to analyse the sensitivity of the WFH probability. The results suggest that socioeconomic characteristics such as occupation or income have a high influence on the probability to WFH. Travel time by the different modes of transport does not have such a significant influence on the probability to WFH as do the number of cars per adult in the household, if they work in the city centre or if they have their own space/room to WFH, which we suggest is partly linked to reduced commuting activity over a typical work week.

Results of this study also suggest that underlying attitudes do have a statistically significant influence on the probability to WFH or to commute by PT, car or other modes. In terms of WFH, one of the most relevant attributes was the workplace policy towards WFH, and in terms of the use of PT, if respondents could get on public transport when they wanted or they needed to queue longer than prior to COVID-19. These findings are useful behavioural inputs in developing guidelines by transport authorities on issues to think through how best to improve the messaging on the bio-security safety of using public transport, with greater concerns evidence at the stops and stations in contrast to on public transport. Indeed, in Australia, mask wearing is not mandated while waiting for public transport but is required on public transport.

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Appendix

Table 10: Elasticities Hybrid Choice Model

Alternative probability	Variable	Mean	Std error
WFH	Has own space or room to work from home (1,0)	0.135	0.003
WFH	My workplace is directing me to work from home (1,0)	0.180	0.008
WFH	My workplace gives me the choice to work from home (1,0)	0.265	0.007
WFH	Female (1,0)	-0.073	0.001
WFH	Personal income ('000$AUD)	0.302	0.004
WFH	Number of individuals per household	0.284	0.003
WFH	Number of cars per person in household	-0.102	0.002
WFH	Monday (1,0)	0.392	0.017
WFH	Tuesday (1,0)	0.385	0.017
WFH	Wednesday (1,0)	0.375	0.016
WFH	Thursday (1,0)	0.376	0.016
WFH	Friday (1,0)	0.375	0.016
WFH	Workplace located in CBD (1,0)	0.030	0.001
WFH	Workplace located in New South Wales (1,0)	0.302	0.004
Car driver	In-vehicle travel time (mins)	-0.033	0.001
Car driver	Cost (AUD$)	-0.091	0.004
Taxi/rideshare	In-vehicle travel time (mins)	-0.026	0.001
Taxi/rideshare	Cost (AUD$)	-0.225	0.010
Train	Last time I used public transport I got on when I wanted (1,0)	0.122	0.002
Train	In-vehicle travel time (mins)	-0.050	0.001
Train	Cost (AUD$)	-0.042	0.001
Train	Access, egress and waiting time (mins)	-0.124	0.003
Bus	Last time I used public transport I got on when I wanted (1,0)	0.096	0.001
Bus	In-vehicle travel time (mins)	-0.070	0.002
Bus	Cost (AUD$)	-0.046	0.003
Bus	Access, egress and waiting time (mins)	-0.133	0.004
Light rail	Last time I used public transport I got on when I wanted (1,0)	0.122	0.002
Light rail	In-vehicle travel time (mins)	-0.006	0.000
Light rail	Cost (AUD$)	-0.005	0.000
Light rail	Access, egress and waiting time (mins)	-0.018	0.001
Light rail	Cost (AUD$)	0.122	0.002
Ferry	In-vehicle travel time (mins)	-0.002	0.000
Ferry	Cost (AUD$)	-0.002	0.000
Ferry	Access, egress and waiting time (mins)	-0.008	0.001
Walk	Travel time active modes (mins)	-0.280	0.010
Bicycle	Travel time active modes (mins)	-0.150	0.009
Motorcycle	In-vehicle travel time (mins)	-0.005	0.000
Motorcycle	Cost (AUD$)	-0.006	0.001