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Working from home and its implications for strategic transport modelling based on the early days of the COVID-19 pandemic

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A R T I C L E I N F O

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A B S T R A C T

The COVID-19 pandemic has changed the way we go about our daily lives in ways that are unlikely to return to the pre-COVID-19 levels. A key feature of the COVID-19 era is likely to be a rethink of the way we work and the implications this may have on commuting activity. Working from home (WFH) has been the 'new normal' during the period of lockdown, except for essential services that require commuting. In recognition of the new normal as represented by an increasing amount of WFH, this paper develops a model to identify the incidence of WFH and what impact this could have on the amount of weekly one-way commuting trips by car and public transport. Using Wave 1 of an ongoing data collection effort done at the height of the restrictions in March and April 2020 in Australia, we develop a number of days WFH ordered logit model and link it to a zero-inflated Poisson (ZIP) regression model for the number of weekly one-way commuting trips by car and public transport. Scenario analysis is undertaken to highlight the way in which WFH might change the amount of commuting activity when restrictions are relaxed to enable changing patterns of WFH and commuting. The findings will provide one reference point as we continue to undertake similar analysis at different points through time during the pandemic and after when restrictions are effectively removed.

1. Introduction

In the first quarter of 2020, the novel coronavirus - named COVID-19 by the World Health Organisation - began spreading around the world causing widespread illness, disruption and death. At the time of writing this paper (27th of May 2020), approximately 5.4 million cases had been recorded; resulting in 343,514 deaths. The impact of COVID-19 differs dramatically from country to country, and relatively speaking, Australia has done well in combating the spread of the virus, with a total of 7142 cases and 103 deaths being recorded, equivalent to 285 cases and 4.12 deaths per million population.

A large part of the relative success of the Australian response has been the speed at which Australia recognised COVID-19, brought in regulations and associated mandated restrictions to control the spread, and the overarching compliance of the Australian public with both the recommended and regulated approaches (c.f. Beck and Hensher, 2020). The suppression of travel and other activity has been widespread, and the impacts on the transport network have been substantial. Fig. 1 highlights the reduction in (a) the number of trips made per month on major public transport modes, and (b) the average daily vehicle counts on two major roads in the Sydney metropolitan region.

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While travel activity has been reduced, there has been a significantly large uptake in working from home (WFH). While many are still unable to WFH, in a national survey in April 2020 Beck and Hensher (2020) found that the overall number of people working from home at least one day a week had increased from 30% to 60%, and the number working from home five days a week had risen from 7% to 30%.

Thus, one unintended consequence of COVID-19 is that many may now see working from home as a viable option, including employers. While Australia entered working from home in a haphazard manner, there are indications that major organisations are seeing improvements in productivity as a result of working from home (Smith, 2020), with technology companies like Google and Facebook planning to allow, indeed encourage if not mandate, staff to work from home until 2021 if not beyond (Paul, 2020). Research by Gartner (2020) reveals that 74% of Chief Financial Officers are planning to move at least 5% of their previously on-site workforce to permanently remote positions post-COVID-19. Equally, workers are seeing some benefits from this arrangement. A recent global survey conducted by Citrix (2020) showed that 70% of respondents believed their productivity at home to be the same or higher than at the office. One of the biggest advantages is being able to use the time otherwise spent commuting to be more productive, or spend it with family and on leisure activities.

The aim of this paper is to identify, at the height of the restrictions in March and April 2020 in Australia, the incidence of WFH and what impact this was likely to have on the amount of weekly one-way commuting trips by car and public transport. We develop a number of days WFH ordered logit model and link it to a zero-inflated Poisson (ZIP) regression model for the number of weekly one-way commuting trips by car and public transport. Scenario analysis is undertaken to highlight the way in which WFH might change the amount of commuting activity when restrictions are relaxed, to enable changing patterns of WFH and commuting. The findings will provide one reference point as we continue to undertake similar analyses at different points through time during the pandemic, and after when restrictions are effectively removed.

2. Literature review

The increased acceptance of WFH by both employees and employers has important ramifications for the transport network, and has long been seen as a mechanism through which congestion and emissions can be reduced. Telecommuting was a term first coined by Nilles (1976), who proposed the replacement of commuting with "telecommuting" (working at home made possible by technological advances) in response to traffic, sprawl, and scarcity of non-renewable resources. Salomon and Salomon (1984) provide an overview of the nascent literature on telecommuting, with early research focused on white collar workers with particular reference to computer-based information workers. The authors highlight that some studies project a technology-based economy where 50% of white-collar workers would work from home. They questioned whether such projections were valid and suggested the importance of social interaction at work and the need to separate home and work roles which act as important barriers to such scenarios.

Indeed, early sociological research pointed to barriers in the adoption, namely (i) individuals required social interaction inherent in being at work, (ii) had a need to separate or create a buffer between home and work roles, and (iii) felt the need to be visibly present to achieve professional advancement (Salomon, 1986; Hall, 1989). However, telecommuting was a policy lever that gained traction within the world of transportation, initially because it was something that could be implemented quickly, relatively inexpensively, and addressed a variety of public and private sector concerns such as congestion, work-life balance, and facility use (Mokhtarian, 1991).

Pendyala et al. (1991) used travel diaries to explore differences in behaviour before and after telecommuting. They found that telecommuters make proportionately fewer linked trips as a result of few trips being made overall, that they tend to shift activities to

a) Public Transport Patronage **(b) Traffic Counts on Major Roads**

Fig. 1. Impact of COVID-19 Restrictions on the Transport Network.

destinations closer to home, and to make proportionately fewer peak-period trips. Hensher et al. (1994) examined the changing nature of labour force participation and work practices, finding shifts that would likely impact on mobility and road transport needs. Interestingly, they forecast a rise in small freight delivery volumes, and a steady increase in shopping and personal business travel relative to work travel as a result of distributed work practices. In the current pandemic setting, both distributed work practices and these increases are the result of COVID-19.

In response to a call to start thinking about how to incorporate telecommuting and home-based work into the traditional urban travel demand forecasting process (Mokhtarian, 1991), Ben-Akiva et al. (1996) proposed a travel demand modelling framework for the information era. They outlined a three-stage approach to incrementally updating the forecasting process through understanding how lifestyle decisions impact on mobility choices and how both impact on daily activity patterns. While Ben-Akiva et al. (1996) included sampling of both employees and employers, Yen and Mahmassani (1997) included both from the same organisation, and Brewer and Hensher (2000) provided a framework to look at the endogenous nature of the choice to telecommute between the employee and their employer or supervisor. The role of social influence and social contact on telecommuting has also been explored (Wilton et al., 2011). Recent studies that have explored the relationship between the choice and frequency of telecommuting and characteristics of the individual, household, job type and built environment include Sener and Bhat (2011), Singh et al. (2013) and Paleti and Vukovic (2017). Brewer and Hensher (2000) proposed and implemented an interactive agency choice experiment (IACE), in which they involved employees and employers in revealing their joint preferences for distributed work practices. They found that many employees liked the idea but were reticent about how their employers would respond, and surprisingly many employers were supportive once their preferences were revealed to employees, who subsequently revised their position.

In terms of the effect of telecommuting on travel behaviour, Mokhtarian et al. (1995) found that both commute and non-commute travel (measured in person-miles) decreased as a result of telecommuting. Mokhtarian et al. (2004) found that one-way commute distances were longer for telecommuters than for non-telecommuters, but average commute miles overall were less for non-telecommuters due to trip infrequency. Zhu (2012), however, found that telecommuting generated longer one-way commute trips, and also longer and more frequent daily total work trips and total non-work trips, arguing that there is a significant complementary effect of telecommuting on personal travel. Research by Kim et al. (2015) also found that telecommuting can indeed be a complement, particularly when it releases the household vehicle from mandatory work travel, to be used for non-commute trips.

More recently, Shabanpour et al. (2018) examine the choice to telecommute across five broad levels (do not telecommute; a few times a year; once a month; once a week; and almost every day) using a zero-inflated hierarchical ordered probit model. The authors find that, in the sample, 12% of respondents currently have work flexibility (defined as the ability to adjust their work schedule or not), and that such flexibility has positive impacts on both the potential to telecommute (to make telecommute at some level) and the level incidence of telecommuting (how often they do so). Using their model of telecommuting participation and frequency, they simulated a scenario where 50% of workers had such work flexibility, and if this were the case it could be possible to reduce total daily vehicle miles travelled (VMT) and vehicle hours travelled (VHT) up to 0.69% and 2.09%, respectively. It should be noted[1] that while telecommuting refers to spatial flexibility, and work flexibility refers to temporal flexibility (and thus are not one and the same), the paper does suggest that those with greater flexibility in their working hours appear to be able to opt into telecommuting more easily. With employers in Australia having seen now that WFH may work (Beck and Hensher, 2020), and indeed is an opportunity to perhaps recoup the estimated $30 billion of productivity lost to congestion (Infrastructure Australia, 2019), WFH may be a more formalised policy for organisations moving forward.

If increased levels of working from home is to be the so called ‘new normal’ as we move beyond COVID-19, there are important ramifications of this changed behaviour for strategic transport models that are used to forecast transport demand and simulate network flows.[2] In response to the potential change in the way people may work and move, this paper develops an approach to identify the incidence of WFH and what impact this is likely to have on the amount of weekly one-way commuting trips by car and public transport, such that the model can be easily integrated into existing strategic model frameworks. Equally, it is important that scenario planning in the short-term be undertaken as we seek to understand how the transport network may respond to the ongoing changes in travel due to COVID-19.

The rest of this paper is structured as follows. In the next section we outline the survey and data collection process, as well as providing some contextual information about when the data was collected. In Section 4, we provide an overview of interesting results from the survey in the context of working from home and travel, followed by the development of a model structure in Section 5, summarising the results from the model in Section 6. In Section 7, we provide scenario analyses to simulate the impact of different working from home conditions, before providing concluding remarks in Section 8.

3. Survey and data collection

Recognising that COVID-19 was impacting on travel and activity patterns, which would again change profoundly as a result of

[1] As highlighted by one anonymous reviewer.

[2] See the sceptical view recently presented by Patricia Mokhtarian.(https://protect-au.mimecast.com/s/LYpCCoV1kpfmVJWmuzuP1A?domain=youtube.com), in which she points out (among other arguments) that employers have had ample previous opportunity, during countless past extreme events, to "see that WFH may work".

increased regulations restricting movements further, a survey was developed in mid-March 2020. The survey[3] asked respondents to provide information on their level of employment prior to the COVID-19 outbreak as well as after, including their ability and instances of working from home. Respondents were then asked to think about weekly travel activity of the household in the early part of March, prior to the emergence of COVID-19 as a significant public health threat, and to complete a short travel activity survey asking them to recall what trips the household made by different modes of transport and for different purposes. They were then asked if the household had changed their travel activity as a result of COVID-19 and if the answer was yes, they completed a second set of travel questions outlining the changed travel. For those that had not changed but had plans to do so, and those who had changed and planned even more, they were asked what their planned change might look like.

The on-line survey was distributed for completion on 23 March 2020. Those initially contacted were a convenience sample based on membership lists of organisations associated with the Institute of Transport and Logistics Studies,[4] along with members of the Institute email list itself. A convenience sample was used as, along with many universities globally, the University of Sydney froze all spending in response to an uncertain budget position due to COVID-19. For context, Fig. 2 shows the number of COVID-19 cases in Australia (also in the state of New South Wales, and the rest of the country combined).

At the time period at which data was collected, Australia had been staging a series of ever tightening restrictions; on 19 March international borders were closed to non-citizens and permanent residents, on 20 March limits were placed on the size of public gatherings, which were further tightened on the day the survey went into field (23 March). A week into data collection, tighter restrictions on the size of public gatherings (no more than two persons) and travel (essential travel for work, health or exercise) were announced on 29 March coming into effect at midnight on the 30th with border closures in Queensland and Western Australia. A total of 348 respondents submitted a complete set of responses, the majority of which were from the Sydney metropolitan region (299). The average age of respondents is 46 years, with an average household income of $AUD185,398; 63% of the sample are male. It should be noted that data collection is ongoing,[5] and as we achieve more responses, the sample will become increasingly more representative in terms of socio-demographics, but equally as behaviours stabilise across the pre, during and post COVID-19 experiences.

4. Overview of travel activity and work

Within the convenience sample obtained, 17% of respondents reported that the government regulations surrounding COVID-19 had impacted on the availability of their work, with those from the lowest income groups significantly more likely to be affected. This, in part can be explained by the fact that a proportion of the sample completed the survey prior to the strictest of government regulations being enforced. It can equally be due to 89% of the sample also reporting that their work can be completed from home, where women and younger respondents being more likely to be able to work from home, and low income groups less likely.

As shown in Fig. 3, we see a significant drop in average weekly trips for an individual, for all purposes and modes, falling from a little over 25 trips per week down to 10. This fall is consistent with aggregate measures such as those provided by the Google Mobility Report and CityMapper, as well as international studies using GPS tracking (Mobis, 2020). We also see similar proportional and significant drops in trips for car and public transport modes (train, bus and ferry combined), and for commute trips and those for other purposes.

Fig. 4 displays the work from home policy of the organisation in which the respondents worked, the vast majority having either been given the choice to work from home (45%) or have been directed to do so by their employer (43%). The impact of this flexibility can be seen in Fig. 5, where there is very little differentiation in the number of days worked before and after COVID-19 restrictions, and a sizeable fall in the proportion of respondents working zero days from home (from 57% to 11%). Almost half the sample now working from home five days a week (48%). Females report a significantly higher number of average days worked from home, and those in the lowest income group a significantly lower number of average days worked from home than those in high income categories.

Although this is a convenience sample, and likely overstates the ability to work from home relative to the general population, the sample is very relevant for establishing a model structure and investigating how changed working from home conditions could be understood, and how it might impact on travel demand. The sample used in the subsequent modelling sections are the 177 respondents from the Greater Sydney metropolitan area who were in paid work. For these, we have details of all modes used for commuting and network information around distance, zones, times and costs. This sample is illustrative in nature and the models outputs discussed hereafter can easily be updated as more data becomes available.

5. Modelling approach

The focus of this paper is on identifying the relationship between the number of days working from home during the early days of COVID-19 restrictions and the amount of travel associated with commuting to and from the pre-COVID-19 work place (see Fig. 6). As

[3] A PDF of the survey instrument can be provided on request. It is noteworthy that we provided the same survey to colleagues in Chile and South Africa who are part of the Volvo Research and Education Foundation Bus Rapid Transit (BRT+) Centre.

[4] This list has over 4,000 email addresses and is a broad cross-section of the professional community in government, business and academia, mainly in Australia.

[5] With five more waves planned over a 6-to-8-month period.

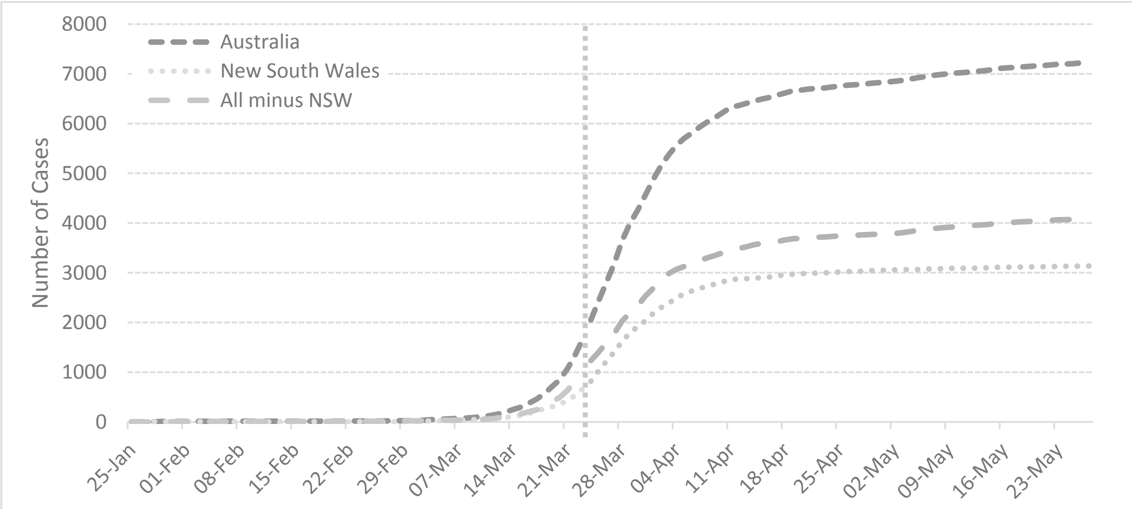


Fig. 2. COVID-19 Cases Before and After Survey Distribution.

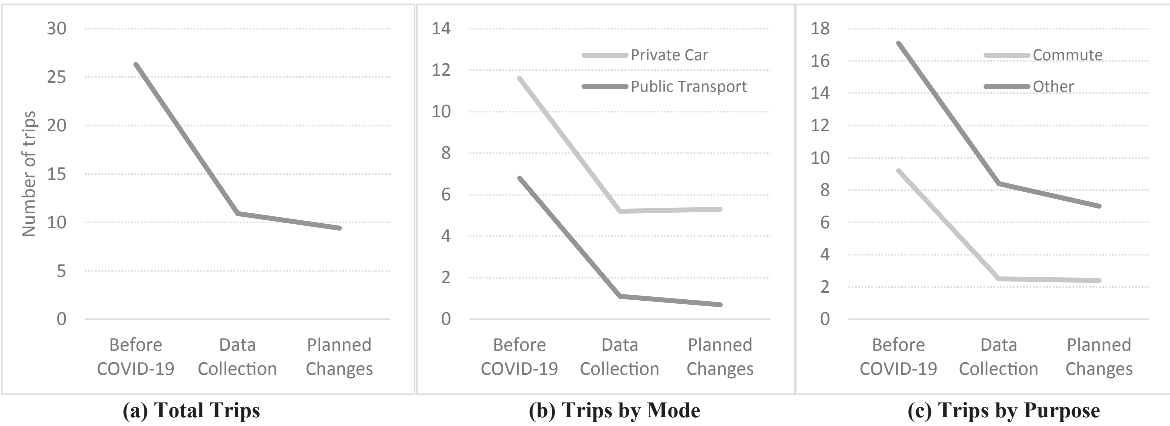


Fig. 3. Changes in Per-person Average Weekly Trips.

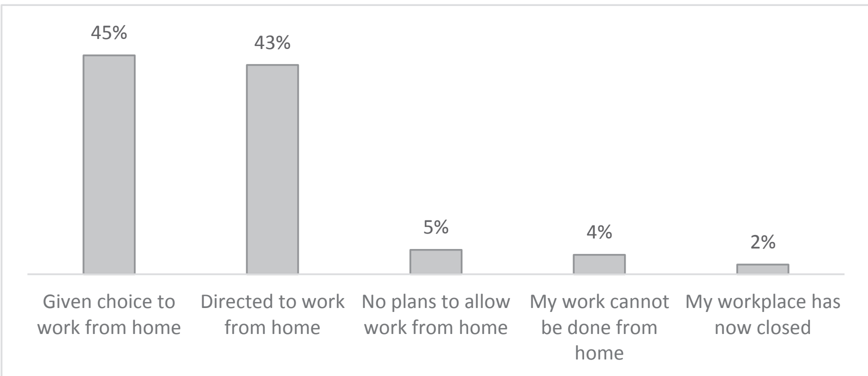
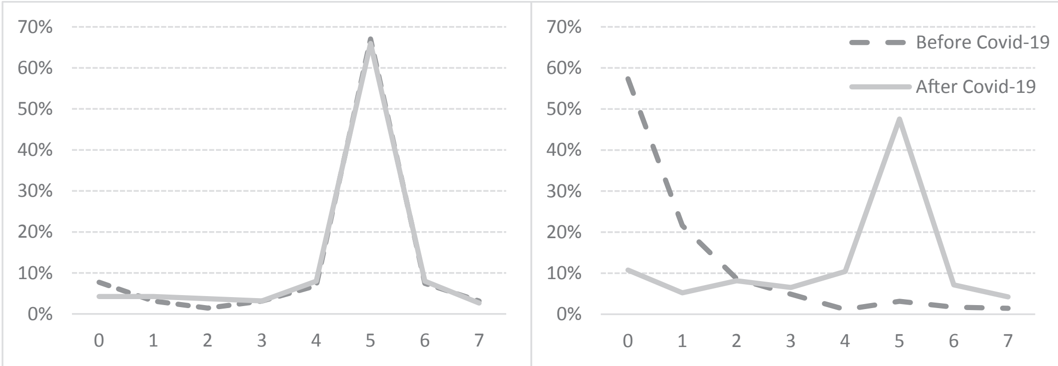


Fig. 4. Work from Home Policy of Employer.



(a) Number of Days Worked **(b) Days Worked From Home**

Fig. 5. Impact of COVID-19 on Work and Work from Home.

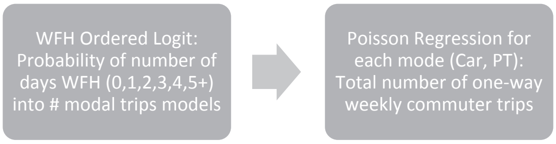


Fig. 6. The Model System.

might be expected, and as shown above, the amount of commuting activity outside of the home was severely curtailed either by choice or by government restrictions.[6] Two models are proposed as an appropriate framework within which to study these behavioural linkages.[7] The first represents the number of days each week (defined as 7 days to include weekends) WFH, specified as an ordered choice model of the logit form. WFH has a natural ordering and hence can be defined by a dependent variable taking the values from 0 up to the maximum number of days of WFH (noting later that we defined the last category as 5–7 days given the small amount of non-zero weekend WFH activity). The second model defines the number of one-way weekly commuting trips by each mode. Recognising the count data nature of the number of trips, a Poisson regression is proposed. The predicted probability of the number of days WFH obtained from the ordered logit model is fed into separate Poisson regression models for one-way weekly car and one-way weekly public transport commuting trips. Estimation at both steps is consistent; however we need to correct the estimated asymptotic covariance matrix for the estimator at step 2 for the randomness of the estimator carried forward from the ordered logit WFH choice model. The standard Murphy and Topel (1985) correction was implemented, so that the standard errors and hence the t-values of the Poisson model are asymptotically efficient.

We discuss in more detail the ordered logit model and the Poisson Regression of the zero inflation (ZIP) form, and then present the final models.

The ordered logit model allows one to include an ordinal dependent variable into the choice model in a way that explicitly recognises the ordinality, and which avoids arbitrary assumptions about scale. It does this by defining points on the *observed scale* as thresholds that recognise, in preference space, that the numerical levels of the dependent variable are not strictly linear (Winship and Mare, 1984; Greene and Hensher, 2010). Formally, let Y_i^* denote an unobserved (or latent) continuous variable that represents the latent continuous tendency to work from home for more days ($-\infty < Y_i^* < +\infty$), defined in utility space; $\mu_{-1}, \mu_0, \mu_1, \ldots, \mu_{J-1}$ denote the threshold utility points in the distribution of Y_i^*, where $\mu_{-1} = -\infty$ and $\mu_{J-1} = +\infty$.

Now, define Y_i to be an ordinal (observed) variable for WFH such that $Y_i = j$ if $\mu_{j-1} < Y_i^* \le \mu_j$; $j = 0,1,2,\ldots,J$ response levels. Since Y_i^* is not observed, its mean and variance are not separately identifiable from the β and μ parameters. For ease of interpretation, we fix its mean at 0 and its variance at 1. To make the model operational, we need to define a relationship between Y_i^* and Y_i. The ordered choice model is based on a latent regression model given as Eq. (1).

[6] The number of daily one-way trips using public transport in the Sydney metropolitan area declined to 27.7 percent of its pre-COVID-19 levels (from 2.2 million to 600,000). These figures refer to all trip purposes and we expect that commuting activity decreased even more.

[7] A referee made the comment "In most cases, can we not guess the number of commute trips by just subtracting the number of WFH days? Are they not just perfect substitutes in most cases?" This is not the case as we now explain. Specifically, we are looking at the number of commuting trips separately by car and by public transport, and thus knowing the number of days WFH (e.g., 3), does not mean that the balance of 2 days are all commuting by car or all by public transport; and indeed on some days they do not work at all (people who work 4 days a week, for example). There are a few people who use public transport to go to work and are picked up by car to go home. The pairwise correlations are -0.45 for #days WFH and # car trips and −0.28 for #days WFH and # public transport trips.

$$Y_i^* = \beta\text{'}\mathbf{x}_i + \varepsilon_i, \varepsilon_i \sim F(\varepsilon_i|\theta), E(\varepsilon_i) = 0, \mathrm{Var}(\varepsilon_i) = 1 \tag{1}$$

where $\boldsymbol{\theta}$ collects the mean and threshold parameters.[8] The observation mechanism results from a complete censoring of the latent dependent variable as follows:

$$\begin{aligned} Y_i &= 0 \text{ if } Y_i^* \leqslant \mu_0, \\ &= 1 \text{ if } \mu_0 < Y_i^* \leqslant \mu_1, \\ &= 2 \text{ if } \mu_1 < Y_i^* \leqslant \mu_2, \\ &\cdots \\ &= J \text{ if } Y_i^* > \mu_{J-1}. \end{aligned} \tag{2}$$

The probabilities which enter the log likelihood function are given by Eqs. (3) and (4).

$$\mathrm{Prob}(Y_i = j) = \mathrm{Prob}(Y_i^* \text{ is in the } jth \text{ range}) \tag{3}$$

$$= F(\mu_j - \beta\text{'}\mathbf{x}_i) - F(\mu_{j-1} - \beta\text{'}\mathbf{x}_i), \quad j = 0, 1, \cdots, J \tag{4}$$

A direct interpretation of the parameter estimates from the ordered logit model is not informative, given the logit transformation of the choice dependent variable. Therefore, we provide the marginal or partial effects which have substantive behavioural meaning, defined as the derivatives of the choice probabilities (Hensher et al., 2015). An extension of the partial effects yields the well-known elasticity estimates. A marginal effect is the instantaneous rate of change in the probability of selecting a particular outcome, with respect to a continuous-valued explanatory variable, *ceteris paribus*. For dummy (1, 0) variables, which are the main variables in the models below, the marginal effects are discrete changes in the probabilities given a change in the dummy variable from 0 to 1. The marginal effects need not have the same sign as the model parameters. Hence, the statistical significance of an estimated parameter does not imply the same significance for the marginal effect.

The marginal effect for a continuous variable in an ordered logit model is $\frac{\partial E[y_i|\mathbf{x}_i]}{\partial \mathbf{x}_i} = \Lambda(\gamma'\mathbf{x}_i)[1 - \Lambda(\gamma'\mathbf{x}_i)]\gamma$. Λ is the logistics distribution $\Lambda(t) = \exp(t)/[1 + \exp(t)]$.

The marginal effect for a dummy variable = $[\mathrm{Prob}(y_i = 1|\overline{\mathbf{x}}_{(d)}, d_i = 1)] - [\mathrm{Prob}(y_i = 1|\overline{\mathbf{x}}_{(d)}, d_i = 0)]$, where $\overline{\mathbf{x}}_{(d)}$, denotes the means of all the other variables in the model.

In contrast to the ordinal specification of WFH, the number of weekly one way trips by car and public transport is a positive number compliant with a count model such as zero inflation Poisson (ZIP) with latent heterogeneity.[9] As a non-negative discrete count value, with truncation at zero, discrete random variable, *Y*, observed over a period of length T_n (i.e., a 7 day week) and observed trips, y_n, (where *n* refers to the n^{th} respondent), the Poisson regression model is given as Eq. (5).

$$Prob(Y = y_n|x_n) = \frac{exp(-\lambda_n)\lambda_n^{y_n}}{y_n'!}, y_n = 0, 1, \ldots; log\lambda_n = \beta' \mathrm{x_n} \tag{5}$$

In this model, λ_n is both the mean and variance of y_n; $E[y_n|\mathbf{x}_n] = \lambda_n$. We allow for unobserved heterogeneity as well as consider the ZIP form for count data (see Greene, 2003) to recognise the possibility of partial observability if data on weekly one-way trips being observed, exhibit zero trips. Specifically, the answer 'zero' could arise from two underlying responses. If we were unable to capture any trips, we would only observe a zero; however, the zero may be due to the measurement period (i.e., a particular week) and the response might be some positive number in other periods. In the current data under the pandemic, zero is in the main a legitimate value. We define $z = 0$ if the respondent always worked from home, 1 if a Poisson model applies; y = the response from the Poisson model; then zy = the observed response. The probabilities of the various outcomes in the ZIP model are:

$$Prob[y = 0] = Prob[z = 0] + Prob[z = 1]^* Prob[y = 0|Poisson] \tag{6a}$$

$$Prob[y = r > 0] = Prob[z = 1]^* Prob[y = r|Poisson] \tag{6b}$$

The ZIP model is given as $Y_n = 0$ with probability q_n and $Y_i \sim$ Poisson (λ_n) with probability 1 – q_n so that (Greene, 2017):

$$Prob[y_n = 0] = q_n + [1 - q_n]R_n(0), \ and$$

$$Prob[y_n = r < 0] = [1 - q_n]R_n(r) \tag{7}$$

[8] The number of estimable thresholds is the number of response categories minus one, but collectively the thresholds are not separately identifiable from the constant term in the index function. In this application we have six response categories, so with the NLOGIT estimation package used in this paper, we estimate the constant term plus four additional threshold parameters.

[9] We also proposed and estimated a negative binomial model which is appropriate, like Poisson, for count data. The overall fit and statistical significance of parameters was inferior to Poisson.

where $R_n(y)$ = the Poisson probability $= \frac{exp(-\lambda_n)\lambda_n^{y_n}}{y_n'!}$ and $\lambda_n = exp(\beta' \mathrm{x_n})$. We assume that the ancillary, state probability, q_n, is distributed normal (i.e., ~Normal (υ_i). Let F[υ_i] denote the normal CDF. Then, υ_i can be defined by the form in Eq. (8) labelled the ZIP(τ) model (Greene, 2017, E988).

$$v_n = \tau ln[\lambda_n] = \tau\beta' \mathrm{x_n} \tag{8}$$

Eq. (8) defines a single new parameter τ which may be positive or negative. If there is evidence of zero trips in any observations, then we can expect the τ parameter to be statistically significant; otherwise we default to the Poisson form with normal latent heterogeneity.

6. Model results

6.1. The ordered logit model for the incidence of working from home

The final ordered logit model for WFH is summarised in Table 2. The model was estimated on 177 respondents who had a paid job, and who exhibited a mix of commuting activity and working from home, with some jobs deemed essential outside of the home. Hence, they must commute to some extent.[10]

In selecting and testing candidate explanatory variables, we wanted to identify influences on WFH that related to an employee's situation where they could choose to WFH or otherwise and the position supported by their employer under government restrictions in the early days of the COVID-19 lockdown. We were also mindful of the need to include variables that could be used in applications that are representative of the socioeconomic characteristic of respondents, which can be used to identify classes of employees who are more likely to WFH either because they chose to and/or their employer allows it.[11] This is especially important as we continue to collect data during the COVID-19 period to see when the WFH profile starts to stabilise and becomes an important piece of evidence in building in this feature to strategic transport planning models.[12]

The evidence in this paper is limited to the Wave 1 data, and although we anticipate richer data as we continue to repeat the survey over five more waves, this information has enabled us to obtain some behaviourally appealing models. A descriptive profile of the data is summarised in Table 1, for the top six occupation classes that represent 95.1% of the sample, noting that we specifically targeted professionals instead of a general population. Given the influence of occupation, we also present the incidence of WFH in Fig. 7 for all eight classes. Despite the sample being a convenience sample, and relatively small, the average age of 45.9 (standard deviation of 15) compares well with a representative sample mean of 46.3 (standard deviation of 17.5). The gender mix has a higher percentage of males (65%) compared to 50% in the general population.

There are three statistically significant employer-policy dummy variables, namely (i) an employee having a choice to work from home pre-COVID-19, (ii) an employer directs the employee to work from home during COVID-19, and (iii) the type of work undertaken by the employee can be completed from home.[13]

All three dummy variables have positive parameter estimates, indicating that Y*, the latent continuous tendency to work from home more days, increases when each of these policy settings are on offer, or that the probability of WFH zero days decreases and the probability of WFH 5 or more days increases while the probabilities of intermediate choices are ambiguous (Greene, 2003) when each of these policy settings are on offer. We tested all available socioeconomic characteristics (i.e., occupation, age, gender and household income) and found that occupation was the best indicator for establishing the extent to which WFH occurred (see Table 2). We used the Australian Bureaus of Statistics 8-category Classification[14] and found that six of the eight occupation categories were statistically significant relative to Machine Operators and Drivers, and Labourers, both of which were set to zero for the dummy variable definition. All six occupation classes are statistically significant with positive parameter estimates. We also used the Brant Test (see Greene and Hensher, 2010) to test the null hypothesis that $\beta_0 - \beta_1 = \boldsymbol{0}$, $\beta_0 - \beta_2 = \boldsymbol{0}$, etc. We implemented the test, but did not find any evidence on the Chi-square test to reject the null hypothesis of equality of parameter estimates.

[10] This distinction is ambiguous, since there are essential tasks that can be done from home (e.g., call centre type work) in contrast to someone involved in looking after aged people in a retirement village or driving a bus or train. We have not used this distinction in the model estimation given it is so ambiguous.

[11] We did investigate random thresholds with systematic socioeconomic influences and tested for age, gender and household income, but did not find any statistically significant effects. This may be due, as is always possible, to the nature of the specific sample; however we will investigate this matter gain when we have future waves of data that are to be sampled from the wider population throughout Australia.

[12] The pre-COVID-19 strategic transport model system might have to be changed to reflect the conditions during COVID-19 in response to network performance, especially travel times and a high incidence of free flow travel times on the road network. Also to the extent to which existing parameters associated with the demand side model system (e.g., levels of service parameters in mode choice models), are sufficiently robust to accommodate significant new levels of service which did not exist when such models were estimated and calibrated.

[13] While it is true that the reported percentage in Fig. 4 were directed by their employer to WFH, many workers were still allowed to do a small amount of work elsewhere. By accounting for the degree of enforcement through explanatory variables in Table 2, we are able to account for the degree of 'no choice' in the sample; however it is clear than many were indeed able to exercise a choice themselves.

[14] https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/6102.0.55.001~Feb%202018~Main%20Features~Classifications%20Used%20in%20Labour%20Statistics~15

Table 1
Descriptive Profile of WFH Model Variables on the 177 workers During COVID-19 (late March 2020).

Variable	Units	Mean (SD)
Number of days working from home per week	Number	3.86 (1.74)
Have a choice to work from home pre-COVID-19	1,0	0.497
Employer directs employee to work from home post-COVID-19	1,0	0.395
Type of work can be completed from home	1,0	0.904
Manager	1,0	0.133
Professional	1,0	0.588
Technicians and trades	1,0	0.067
Community and personal services	1,0	0.024
Clerical and administration	1,0	0.097
Sales	1,0	0.042

Table 2
Ordered Logit Choice model for WFH.

Variable	Units	Estimated parameter (t-value)	95% confidence interval
Constant		−3.0494 (-6.81)	−3.927 to −2.171
Have a choice to work from home pre-COVID-19	1,0	1.8874 (6.72)	1.336 to 2.437
Employer directs employee to work from home during -COVID-19	1,0	2.8918 (9.55)	2.297–3.485
Type of work can be completed from home	1,0	3.5363 (8.28)	2.699–4.373
Occupation (ABS 8 classes):			
Manager	1,0	0.7449 (2.85)	0.232–1.257
Professional	1,0	0.5403 (3.51)	0.238–0.842
Technicians and trades	1,0	1.1677 (2.51)	0.256–2.079
Community and personal services	1,0	4.2600 (5.18)	2.928–5.528
Clerical and administration	1,0	4.2287 (6.38)	2.928–5.528
Sales	1,0	3.3695 (4.84)	2.004–4.734
Threshold parameters:			
μ_1		0.6975 (9.05)	0.546–0.848
μ_2		1.3068 (16.3)	1.149–1.464
μ_3		1.7652 (22.3)	1.609–1.920
μ_4		2.4215 (28.1)	2.252–2.590
Goodness of Fit:			
Log-likelihood at zero betas		−1351.56	
Log-likelihood at convergence		−1145.03	

Note: Mean probability of number of days per week WFH are 0.116 (0 days), 0.051 (1 day), 0.064 (2 days), 0.062 (3 days), 0.10 (4 days) and 0.598 (5 days or more), 177 respondents.

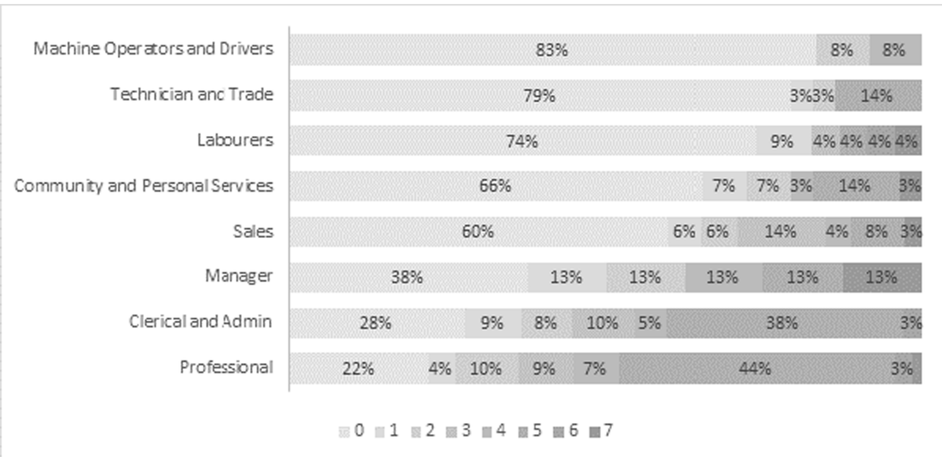


Fig. 7. Number of Days Worked from Home in Last Week by Occupation for the 177 workers (Note: Each row sums to 100%).

Furthermore, for linking the WFH model to the trip frequency model under COVID-19, we had to calculate the probability of choosing[15] a number of days WFH.[16] The probability of each WFH level is shown in Fig. 8, where as we know the dominance of zero (0.116) and 5 days (0.598) WFH exists. We expected this during the restriction period since those whose work is not deemed 'essential'[17] were asked to stay at home, although this mandate from government was interpreted very broadly to include staying at home and WFH.

Although the parameter estimates are statistically significant, they are not behaviourally very interesting; instead, care must be taken in interpreting the numerical magnitude of each parameter estimate since they are non-comparable in this logit non-linear form (as suggested in the model specification section). In Table 3 we present partial (or marginal) effects and elasticities as a way of meaningfully comparing the influence of each explanatory variable on WFH. The behavioural sensitivity of the probability of WFH for each of the explanatory variables can be given by an elasticity or partial effects indicator (Greene and Hensher, 2010). For the logit form, the elasticity of the probability is given in Eq. (10) which is related to the partial (or marginal) effect in Eq. (11), noting that we have dropped the subscript for a respondent (i.e., n).

$$\frac{\partial log P(y|x)}{\partial log x_k} = \frac{x_k}{P(y|x)} \times \frac{\partial P(y|x)}{\partial x_k} = \frac{x_k}{P(y|x)} \times marginal\ effect \tag{10}$$

The marginal effect was defined in Section 5.

In Table 3, the partial and elasticity estimates are generally greater and negative for the three employment policy variables when there is no WFH. They also decline in magnitude while becoming positive in sign for situations where there is no commuting and WFH occurs five or more days per week. Looking at 'have a choice to work from home pre-COVID-19′, all other influences being held constant, since this is a dummy (binary) variable, the pseudo-elasticity of −3.5 is the average percentage change in probability of WFH 0 days associated with the change from not having a choice to WFH to having the choice. If you have a higher opportunity to WFH pre-COVID-19, then you are more likely to WFH 5 + days per week (the positive and higher elasticity estimate of +0.55).

The marginal effect parameter for this variable is −0.1095 which is specifically for the 0 days WFH alternative, being the average change in actual probability when the variable changes from 0 to 1. This is also supported by the fact that all those numbers add to zero across each row of Table 3, indicating the redistribution of probabilities across the alternatives while keeping the sum of all probabilities fixed at 1.

The same calculations can be undertaken for each variable and WFH response level. The behavioural sensitivity associated with each explanatory variable is presented in more detail in a later section where we assess various scenarios.

6.2. The Poisson regression model results for commuting activity

Turning to the Poisson regression exercise, first a descriptive profile of the data is given in Table 4.

The Poisson regression models results are shown in Table 5. With the number of weekly one-way modal trips defined as an integer for the Poisson count model, the overall goodness of fit of the two models are excellent for a non-linear model, varying from 0.48 to 0.50. The tau (τ) parameter (Eq. (8)) associated with the zero inflated Poisson model with normal heterogeneity was statistically significant in all three models, as was the sigma (σ) parameter for both models, the standard deviation of heterogeneity, which is statistically significant at the 1 percent level. The Vuong statistics of 13.71 for car and 8.77 for public transport suggest that the estimated extended Poisson model is favoured over an unaltered Poisson model, hence censoring using Probit. That is, the dependent variable is over-dispersed and has an excessive number of zeros.

Poisson regression models the natural logarithm of the expected number of weekly trips as a function of the predictor variables, and thus we interpret an estimated parameter as follows (Wooldridge, 2002): for a one unit change in the predictor variable, the difference in the natural logarithms of expected counts is expected to change by the respective parameter, given the other predictor variables in the model are held constant. For a binary variable such as gender, the difference in the logs of expected number of weekly car trips is expected to be 0.509 higher for males compared to females, *ceteris paribus*. For a continuous explanatory variable such as the probability of WFH 4 or 5 plus days, if a commuter were to increase the probability of WFH 4 or 5 plus days by from say 0.1 to 0.2, the difference in the natural logarithms of expected number of weekly car trips would be expected to decrease by 2.1443, *ceteris paribus*. The same logic, but for an increase, occurs for the probability of WFH 2 or 3 days a week; however, the positive sign can be explained as follows. In the sample, there were few respondents who did not work from home at all; hence the comparison is mainly between 2–3 days, and 4 to 5 plus days WFH and hence the positive sign. Likewise, as age increases by 1 year, the difference in the natural

[15] The formula used for the ordered logit model is different to a standard unordered labelled choice model. An example for four alternatives is:$U_{fit} = b(1)+b(2)*x1+b(3)*x_2$ where this is the utility expression for a constant and 2 explanatory variables;$f_0=exp(-U_{fit})/(1+exp(-U_{fit}))$;$f_1=exp(\mu_1- U_{fit})/(1+exp(\mu_1- U_{fit}))$;$f_2=exp(\mu_2- U_{fit})/(1+exp(\mu_2- U_{fit}))$;$p_0=f_0$; $p1=f_1-f_0$; $p2=f_2-f_1$; $p3=1-f_{2;\ and}$ the expected value of Y (or P_{model})$p_{model}=(y=0)*p0 + (y=1)*p1 + (y=2)*p2 + (y=3)*p3$, where p= the choice probability for that level.

[16] Another possible set of models includes a commuter mode choice model; however, in the COVID-19 period with so little commuting (indeed many respondents undertook zero commuting activity), such a model is both uninformative and problematic to estimate because too many people did not 'choose' any modes for commuting. The WFH model is in one sense a reflection of an alternative in a mode choice model, namely no modes chosen. We did attempt to estimate such a model using free flow travel tines and modal cost data, but decided to put this on hold until we start to see a return to some amount of commuting activity.

[17] The word 'essential' was used by the Prime Minister to determine who should go to work and who should stay at home.

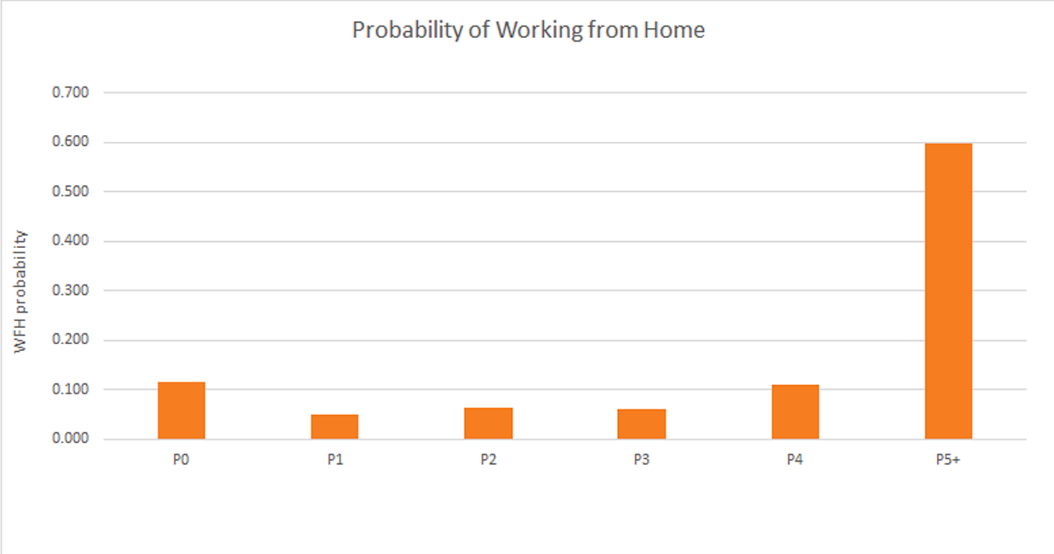


Fig. 8. The incidence of days per week WFH.

Table 3
Direct elasticity of choice and partial effects.

Working from Home Days per week:	*0*	*1*	*2*	*3*	*4*	*5 or more*
Have a choice to work from home pre-COVID-19	−3.50 (−0.109)	−2.86 (−0.080)	−2.25 (−0.092)	−1.65 (−0.071)	−0.93 (−0.074)	0.55 (0.425)
Employer directs employee to work from home during COVID-19	−4.70 (−0.147)	−3.75 (−0.105)	−2.93 (−0.119)	−2.18 (−0.093)	−1.37 (−0.109)	0.74 (0.573)
Type of work can be completed from home	−17.7 (−0.552)	−4.09 (−0.115)	−1.01 (−0.041)	0.27 (0.012)	0.97 (0.077)	0.80 (0.619)
Occupation (ABS 8 classes):						
Manager	−0.97 (−0.030)	−0.97 (−0.026)	−0.83 (−0.034)	−0.72 (−0.031)	−0.54 (−0.043)	0.21 (0.163)
Professional	−0.85 (−0.027)	−0.77 (−0.022)	−0.67 (−0.027)	−0.54 (−0.023)	−0.35 (−0.028)	0.16 (0.126)
Technicians and trades	−1.26 (−0.039)	−1.21 (−0.034)	−1.14 (−0.046)	−1.04 (−0.045)	−0.86 (−0.068)	0.30 (0.233)
Community and personal services	−1.85 (−0.058)	−1.84 (−0.052)	−1.84 (−0.075)	−1.82 (−0.078)	−1.78 (−0.141)	0.52 (0.403)
Clerical and administration	−2.12 (−0.066)	−2.07 (−0.058)	−2.02 (−0.082)	−1.95 (−0.084)	−1.84 (−0.146)	0.56 (0.436)
Sales	−1.86 (−0.058)	−1.84 (−0.052)	−1.82 (−0.074)	−1.78 (−0.076)	−1.71 (−0.136)	0.51 (0.395)

Note: Measures are associated with the number of days WFH with respect to given variable (partial or marginal effects in brackets).
Note: The elasticity as a percent change = partial effect/probability of WFH for that response level. All elasticities are statistically significant at 95 percent confidence level or better with the exception of 'Type of work can be completed from home' for WFH = 3 days. They are weighted averages, across the sample, of the individual-specific elasticities, with weights being the probability of the level of WFH being chosen.

Table 4
Descriptive profile of commuter trips model variables.

Variable		*Car*	*Public Transport*
Number of one-way weekly trips	Number	1.266 (3.02)	0.689 (2.34)
Age	Years	43.13	
Male	1,0	0.62	
Probability of WFH 2 or 3 days per week	1,0	0.126	
Probability of WFH 4 or 5 plus days per week	1,0	0.707	

Table 5
Influence of WFH on Number of Weekly One-way Modal Commuter Trips.

One-way weekly commuting trips:	*Car*	*Public Transport*
Constant	0.6301 (1.57)	−0.5512 (−0.60)
Age (years)	0.0206 (4.43)	0.0260 (1.98)
Male (1,0)	0.5090 (3.96)	–
Probability WFH 2 or 3 days per week	3.5705 (2.77)	11.0166 (4.30)
Probability WFH 4 or 5 plus days per week	−2.1443 (−6.02)	−3.2650 (−4.88)
Tau	0.2194 (5.10)	0.5204 (6.46)
Sigma (latent heterogeneity)	0.6996 (10.6)	1.0834 (4.62)
Goodness of Fit:		
Pseudo R^2	0.480	0.500
Vuong stat vs Poisson	13.71*	8.77*
Partial Effects:		
Age (years)	0.0199 (4.41)	0.008 (2.21)
Male (1,0)	0.4915 (3.83)	–
Probability WFH 2 or 3 days per week	3.447 (2.94)	3.369 (2.58)
Probability WFH 4 or 5 plus days per week	−2.070 (−5.79)	−0.999 (−2.61)

Note: t-value in brackets for parameter estimates. * = Vuong test favours extended model; Murphy and Topel correction of standard errors.

logarithms of the expected number of weekly car trips would be expected to increase by 0.0206, *ceteris paribus*.

Again, like the ordered logit model, a more informed way of illustrating the behavioural response associated with changes in the probability of WFH, age and gender is to undertake a number of scenario applications, which we now present and discuss in the following section.

7. Simulating working from home and expected commuting trips

We have selected several scenario examples to illustrate the application of the models.[18] The impact of COVID-19 was simulated to predict the number of WFH days and related number of one-way weekly commuting trips by car and public transport for different scenarios with potential policy implications. The levels of the explanatory variables in the base scenario were set at the sample averages to represent the status of WFH and commuting activity for the period (see Tables 1 and 4). Of particular interest are the findings that 49.72% of respondents could choose whether to work from home and 39.55% were directed by their employers to work from home. 90.4% of the respondents indicated that their work could be performed from home. The average age of the sample respondents was 43 years, with 62% being male.

7.1. Scenario One: All or half of the working people can choose to WFH

Assuming all work can be performed from home instead of the sample average of 90.4%, we tested scenarios where all or half of the employees can freely choose whether to work from home, but no one would be asked to do so by their employers (see Table 6). In the scenario that all employees can choose to WFH, the average number of WFH days would increase from 3.86 to 4.10 days, just a small increase from the base scenario. The average per-person weekly number of commuting trips by car would drop from 1.27 trips to 0.91 trips, and the average per-person weekly number of commuting trips by public transport would drop to 0.34 trips from 0.68 trips. Although these results may not vary greatly in absolute terms, because of the already high levels of WFH in the base (COVID-influenced) scenario, 0.68 to 0.34 is a drop of 50%, and 1.27 to 0.91 is a drop of 28%.[19]

On the other hand, if only 50% of the employees could make these choices, the average number of days working from home would drop substantially from 3.86 days to 3.31 days, the average per-person weekly number of commuting trips by car would increase from 1.27 trips to 1.77 trips, and the average per-person weekly number of commuting trips by public transport would increase from 0.68 to 1.47 trips.

To assess some socioeconomic segment effects, we compared the differences of 30-year-old and 50-year-old employees, both with an even gender split. The models predict that 50-year-old employees would likely undertake more trips compared to the overall group, even more so for the 30-year-old employees. In the base scenario, commuters in the 50-year-old group would on average make 1.36 weekly car trips and 0.81 weekly public transport trips, compared to the 0.95 weekly car trips and 0.50 weekly public transport trips by commuters in the 30-year-old group. The same pattern can be observed in the scenario with all or half of the respondents having a choice to work from home. In both scenarios, commuters in the 50-year-old group are predicted on average to undertake 40% to 60%

[18] We ran a number of scenarios on all explanatory variables for both models but have selected the most interesting results herein. Other results are available on request.

[19] To be clear on how to interpret Table 6, the 50% who hypothetically have the choice in the scenario are randomly assigned to that status, and therefore differ substantially from the specific 49.72% who currently have the choice. The distribution of those who will have the choice to WFH will realistically not be independent of other characteristics pertinent to the frequencies of WFH and of commuting.

Table 6
Impact of all or half of the employees having choices to work from home.

	Current/Base Scenario	*100% can choose to WFH*	*50% can choose to WFH*
Average WFH days	3.86	4.10	3.31
Sample averages:			
Car trips per week	1.27	0.91	1.77
PT trips per week	0.68	0.34	1.47
30 year-old and evenly split males/females:			
Car trips per week	0.95	0.68	1.32
PT trips per week	0.50	0.25	1.09
50 year-old and evenly split males/females:			
Car trips per week	1.36	0.98	1.89
PT trips per week	0.81	0.40	1.71

more weekly trips by car or public transport compared to the 30-year old group.

7.2. Scenario Two: 25% to 100% of the working people are asked to WFH

In the following scenario, we assume that working people cannot choose to work from home but will be directed/asked to work from home by their employer. We then tested to see what the impact would be if 25%, 50%, 75%, and 100% of working people were asked to work from home. As shown in Fig. 9, when the proportion of working people who are asked by their employer to work from home drops from 100% to 25%, the average number of WFH days is predicted to decrease linearly from 4.61 days to 3.09 days a week. Similarly, the average per-person number of weekly commuting trips by car would increase from 0.56 trips to 2.06 trips and the average per-person number of weekly trips by public transport would increase from 0.11 trips to 2.00 trips[20].

Further examination of an increase in the number of one-way weekly commuting trips by car and public transport, shows that both grow exponentially instead of linearly, as shown in Fig. 10.[21] This suggests an increasing rate of change for car and public transport usage when the proportion of the workforce asked to work from home decreases. For example, when the proportion of the workforce directed to work from home drops from 50% to 25%, the average weekly usage of public transport for commuting would increase at a much faster rate than the situation when the WFH proportion decreases from 100% to 75%. This pattern of change to commuting activity is very informative for policymakers in determining possible situations when restrictions are eased, such as keeping the required social distancing and other measures during the pandemic and for periods afterwards.

8. Conclusions

Transport models need to adapt to changes in the way that people live, work and move. New technology and data present opportunities to improve the way that infrastructure and services are planned. The modelling framework presented in this paper is a response to the need to recognise that, in the future, an increasing incidence of working from home is likely to be part of the way in which workers undertake productive work-related activity. In the pre-COVID-19 past, there was limited recognition of the role that WFH played in commuting activity and its impact on the network performance of roads and public transport.

Although distributive work practices (e.g., telecommuting) have existed for many years (Brewer and Hensher, 1998) they have rarely been incorporated into integrated transport and land use (ITLU) model systems; a rare exception is MetroScan (Ho et al., 2017)[22] and its predecessor TRESIS (Hensher and Ton, 2002). Now it is clear that the growing popularity of WFH as proven to some extent through the forced staying at home under the COVID-19 pandemic, must become an important behavioural choice feature of modelling ITLU systems during COVID-19 after all restrictions are removed..

The age-old assumption of focussing on a typical commuting day in modelling modal choice and expanding travel behaviour up to a week and a year is no longer valid, indeed if it ever was. The necessity to develop a model to predict the number of weekly days working from home (as well as the time of day of travel as staggered working hours also change), should now be a priority action. At a population scale we have a policy lever to assist in managing the transport network not observed previously.[23] This is a non-transport polity initiative (WFH) that should be encouraged and supported by government and employers before the opportunity is frittered away and we return to the bad habits that delivered high levels of traffic congestion and crowding in public transport (Beck and Hensher, 2020). This has, however, to be balanced against the desire to ensure that a return to the office and some amount of reduced working from home, does not support the growth in car use at the cost of reduced public transport use (and implications on fare revenue and subsidy support).

[20] The logic in interpreting Table 6 also applies to interpreting Fig. 9.
[21] The Poisson model is non-linear given the exponential functional form.
[22] Although the parameter estimates are unlikely to be appropriate for the post-COVID-19 context.
[23] Flextime and compressed work schedules have been promoted as transportation demand management strategies for decades, as has working from home, but the incidence of its occurrence has been very small compared to what we are witnessing during the COVID-19 pandemic.

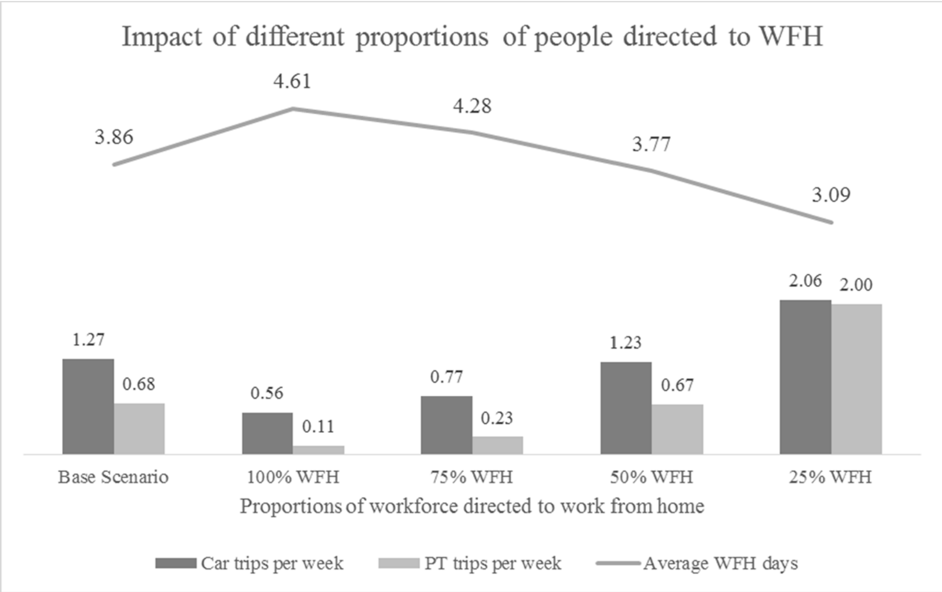


Fig. 9. Impact of different proportions of people directed to WFH.

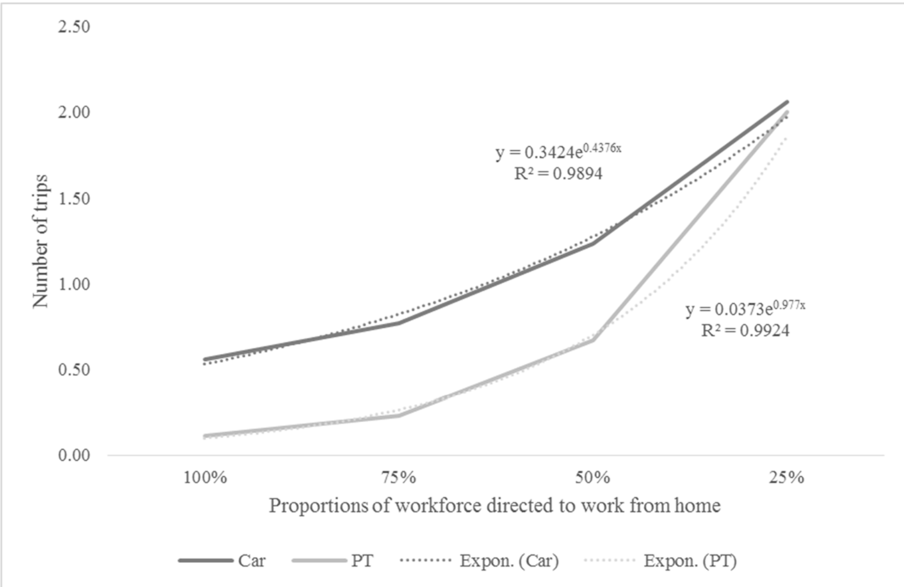


Fig. 10. The increase in the per-person weekly trips with a decrease in the incidence of WFH.

The modelling framework proposed and implemented in this paper draws on new data collected at the height of restrictions associated with COVID-19, wherein we observed a significant cessation in commuting (often being zero travel activity). This was in part a response to government mandating staying at home unless going to work where work was essential and could not be performed from home (with a fine over $1,000 if an individual contravened the mandate and $5,000 for businesses). But it is also a directive from an employer or the ability to exercise a choice that was already available. The data enabled us to estimate models to predict the probability of WFH and what this would mean for the predicted number of weekly one-way commuting trips by car and public transport.

What we have in the models herein might be best described as the extreme response to the pandemic, with significant reductions in modal commuting activity and an associated high incidence of WFH all the time. As a consequence, the data collected just in Wave 1, has limitations in respect of the transferability of the evidence to time points over the next months. Possibly longer, as restrictions are slowly lifted and some amount on return to commuting and working away from home occurs, including the pressures off of families who had to school their children from home.

In ongoing research, we are collecting additional waves of data on a progressively longer gap between waves, with Wave 2 completed in late May and Wave 3 that begun in late June 2020. The models presented in this paper can then be revisited and updated as new data and stabilising commuting patterns as well as WFH regimes settle down. This should not change the types of models developed, but may include an additional commuter mode choice model (as discussed in footnote 16) as well as updated parameter estimates for the WFH model and the commuter trips models. The additional waves of data, up to at least early 2021, should enable us to establish some likely equilibrium in respect of network performance and WFH regimes. When this occurs, a full integration into existing strategic transport model systems should be undertaken. Efforts to undertake such a task prior to this outcome should be supported, but with the caveat that the evidence should be qualified.

Acknowledgments

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