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Accounting for the Location and Allocation of Working Hours throughout the Working Week: A Discrete-Continuous Choice model.

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TITLE: Accounting for the Location and Allocation of Working Hours throughout the Working Week: A Discrete-Continuous Choice model.

ABSTRACT: As COVID-19 becomes a close distant memory for many, we are seeing the impact it has had on where working hours throughout the week are being undertaken. It is not unreasonable to assume that the support for greater flexibility in where work is completed compared to pre-COVID-19 is here to stay and that transport planning needs to move this new pattern of location behaviour centre stage in the revision of strategic transport models. Throughout a seven-day week, we are seeing days in which an individual goes to the main office all day or works from home all day, or undertakes a blended location workday, or does not work at all on a particular day. These four alternatives for each day of the week define a discrete choice model setting which together with the actual hours worked at each location on each day represents a discrete-continuous modelling setting. The paper is interested in identifying where work takes place and the committed hours for each day of the week and treats the seven days of the week as an instantaneous panel. For days where there is commuting involved, we split the discrete alternatives to account for whether commuting occurs during the peak or off-peak period of a day, which is important in terms of the commuting activities in the transport network. We account for the presence of error correlation between the discrete (mixed logit with error components) and continuous (seemingly unrelated regression equations) choices through a selectivity correction for each alternative where it is shown to be statistically significant. A series of direct elasticities provide behaviourally informative evidence on the key drivers of the choice amongst the discrete location alternatives and the continuous choice of hours associated with each. The model system has a very practical feature, in the sense that it can be easily programmed into a strategic transport model system in order to adjust commuting travel activity by mode and time of day in the presence of a more flexible and hence less rigid profiling of when and where work takes place.

KEY WORDS: ***work location, remote working, blended working hours, discrete-continuous choice, allocation of work hours, selectivity correction, elasticities***

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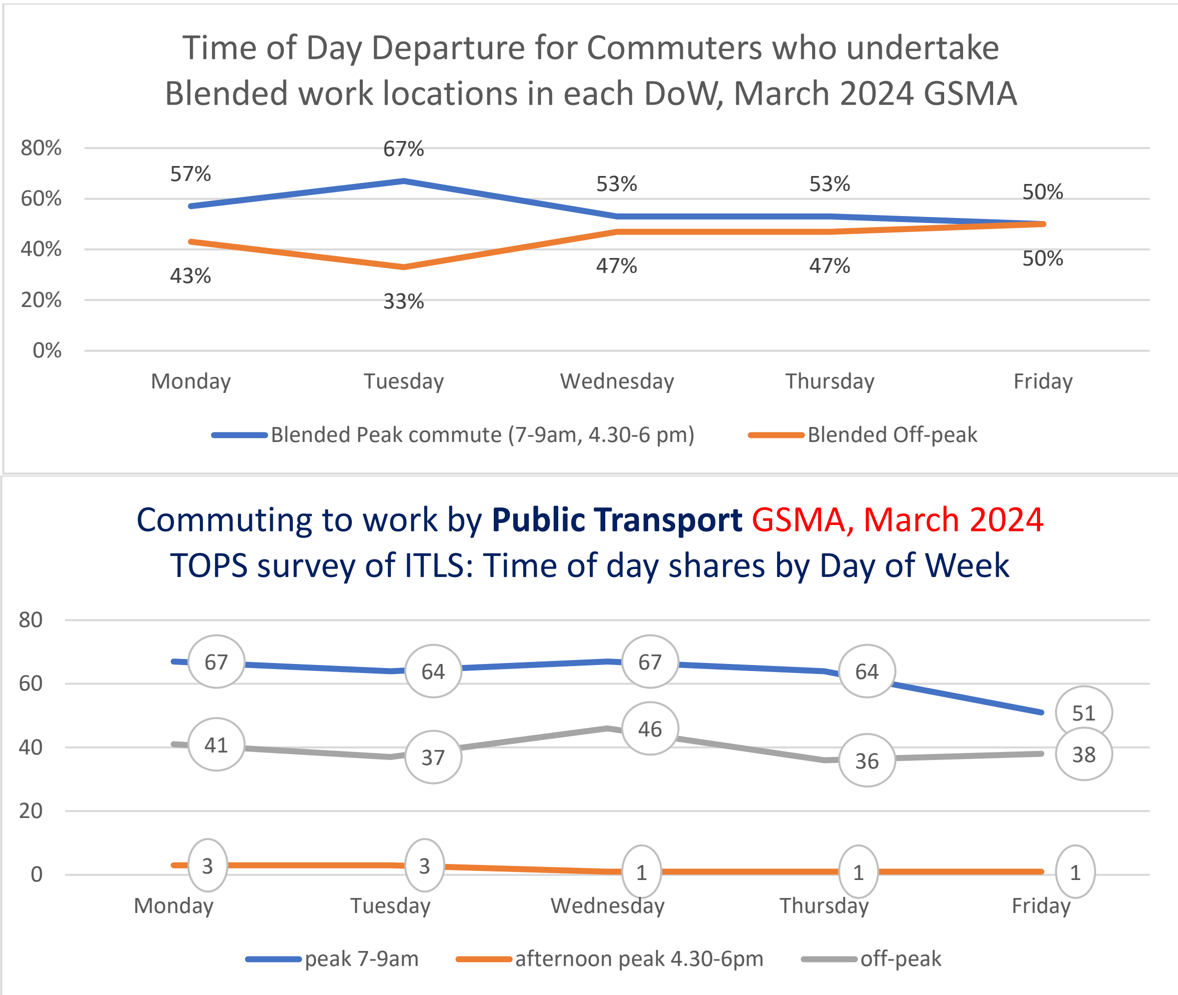
Introduction

Where an individual works and the hours of work undertaken at each location has since Covid-19 transitioned from a dominant main office-based paradigm to one best described as a mixture of working from home (WFH) only and a blended set of workday locations. While there is a slow return to the main office (typically 60% or an average of 3 days per week in Australia), the preference for greater flexibility in where and when an individual works and the high level of acceptance of this new work future by both employees and employers (Hensher et al. 2023a, Beck et al. 2024, Ramani and Bloom 2021, Barrero et al. 2021, Christidis et al. 2021) is being consolidated in an increasing number of geographical jurisdictions. There is not only flexibility in what days of a seven-day week work is undertaken but also in the hours during the day that this occurs.

The idea of a typical working day is no longer relevant, as indeed it never was, despite it being the basis of a great deal of strategic transport modelling systems with expansion up to a week, a month, and a year as if there is almost complete homogeneity in the spatial and temporal patterns of daily work. Commuting is increasingly moving away from the peak period to a mixture of peak and off-peak start times with recent evidence in Australia suggesting a 50:50 split, as illustrated in Figure 1 for the Greater Sydney Metropolitan Area (GSMA) for all commuting trips and public transport[1].



[1] https://www.sydney.edu.au/business/our-research/institute-of-transport-and-logistics-studies/transport-opinion-survey.html

Figure 1: Commuting trips that begin in the peak and off-peak periods in the GSMA in March 2024

The changing composition of work location and hours worked together with the changing time of day that commuting trips commence, suggests a re-appraisal of what this might mean for the performance of the transport network and new opportunities for when and how the broader set of activities undertaken by individuals and households are reframed. Specifically, changing patterns of work impact on when and where other activities such as leisure occur (as shown in Hensher et al. 2022) where we see that the saved commuting time is distributed to increased paid and unpaid work in the home (typically 40%), and leisure in its various guises with one third of the increased leisure time involving out-if home activities and hence travel.

The interest of this paper is in exploring the incidence of take up of different work location patterns during each day of the week, allowing for the time of day of commencement of commuting, where a day involves either working in the main office or a blended set of locations that include the main office and somewhere else (which could be home or other locations), or a day of only working from home (WFH). We also account for days when a worker does not work at all. We also seek to explore the relationship between work location patterns and the hours actually working at these locations on each day of the week, and the key influences on each of these choices.

Given the intrinsic connection between location and hours worked, we set out a discrete-continuous choice modelling system (Hay 1980; Dubin and McFadden 1984) as a mixed logit model with error components for the discrete choice of location profile, and a seemingly unrelated linear regression equations (SURE) for the hours worked at each location by day of the week. In so doing, we account for the presence of error correlation between the discrete and continuous choices via a selectivity correction for each alternative where it is shown to be statistically significant. A series of direct elasticities provide behaviourally informative evidence on the key drivers of the choice amongst the discrete location alternatives and the continuous choice of hours associated with each location.

The paper is structured as follows. We begin with a very brief review of the literature on the changing patterns of working location and hours worked, followed by a summary of the economic theoretical framework that ensures compatibility of the discrete choices defined by an indirect utility function and system of demand equations obtained by the application of Roy's identity so that they are equivalent representations of the individual workers underlying preference ordering. The following section outlines the econometric form of the discrete and continuous choice models and the selectivity correction formula. The data is then identified together with a descriptive profile, followed by the model estimation results, behavioural outputs in the form of elasticities and then concluding remarks.

A Brief Literature Review on Work Location and Saved Commuting Hours

There is an extensive literature on the impact that COVID-19 has had on remote working and especially working from home. It is not the objective of this paper to review that literature, which we and others have extensively done in other publications (e.g. Hensher et al. 2023, 2023a, Heimgartner et al. 2024); however, it should be noted that there have been a variety of approaches adopted in studying the phenomenon of working away from the main office.

A benefit of increased WFH is the reduced amount of weekly commuting time. In the US, Barrero et al. (2020) found that about 35% of the commuting time savings have been redirected to work related to primary employment, and about 60% to household chores and childcare. Hensher et al. (2022) suggest that employees and employers are putting in more hours of work from home that does not necessarily come with increased pay, but also using the opportunity to spend more time with the family and friends, as well as other leisure activities.

During the pandemic, DeFilippis et al. (2020) investigated impacts on worker productivity, and examined data from thousands of companies, concluding that WFH comprises more (but shorter) meetings per day, more emails, and longer workdays. In the UK, it has been shown that WFH productivity is not significantly different from that of workplace productivity but does vary based on socioeconomic status, industry, and occupation (Etheridge et al., 2020). In Australia, perceived work productivity increased as reported by both employees and employers (Hensher et al. 2023a), with approximately 50% of saved commuting time being used in paid or unpaid work from home.

A growing number of studies also found that workers had difficulty in maintaining social interactions via technology but were at the same time apprehensive about returning to the office where social interactions may be perceived as a distraction (Lal et al., 2023). The return to the office has slowly begun but we still see up to 2 days a week WFH for occupations such as professionals, clerical and administrative staff, subject to agreement between the employer and employee (see later section of this paper).

In addition to the many descriptive studies, typified by Beck and Hensher (2020a,b), Barrero et al. (2021) and Etheridge et al. (2020), we have seen a growing number of papers using various statistical and econometric methods to study teleworking in its various guises (e.g., Barbour et al. 2024, Hensher et al. 2024). A recent paper by Asmussen et al. (2024) studies the causal directional relationship between teleworking and commuting distance to the office, concluding that the directionality varies across the population.

Unlike our current study, Asmussen et al. (2024) analyse data at a highly aggregate level defined by the proportion of monthly days that someone worked from home, or the office or a third location, without being able to account for the hybrid nature of work location activity for each day of the week. While their approach is of interest, a more refined detailed daily activity focus can offer a richer perspective when the interest is in integrating a model form into the existing strategic transport planning models used by many metropolitan councils.

The Conditional Indirect Utility Function and its Parent Demand Function

Duality theory in economics can be used to derive a parent function from an indirect utility or demand function (Newman 1987). The original (and still predominant) role of duality theory is to demonstrate that in economic optimization problems, by judicious choice of the parent function, the required response functions of an individual can be derived without the need for explicit optimization (Bryant 2023). Roy's well-known identity has been extensively used in the context of static optimization problems to identify the theoretical underpinnings of an analytically and computationally tractable dual functional form. Typically, in consumer theory, an indirect utility function is specified (in our case for a discrete choice setting) and the application of Roy's identity yields a system of demand equations (for the continuous choices linked to the set of discrete choice alternatives).

The use of duality in the current context requires estimation of *both* the parent function and its dual to ensure that the functional form of the indirect utility function associated with the discrete choice amongst work locations is compatible with the functional form of the utility-maximizing demand for the working hours' function, so that they are equivalent representations of the individual workers underlying preference ordering. Explicit recognition of the interrelationship between work location choice behaviour and the individual’s working hours decision is facilitated by the use of the indirect utility approach. Given the conditional indirect utility specification, we can invoke Roy's identity to produce the utility-maximizing demand for hours worked at each location by day of the week.

The quantum of hours worked is a *net* measure of the amount of activity fulfilment (that is, the extent of consuming final services) after allowing for spatial advantage/disadvantage of work location (that is, a source of disutility). On balance, it is assumed that more working hours are preferred to fewer hours. The regularity conditions imposed on V (the indirect utility form) are continuity, non-decreasing in Y (income), nonincreasing in p (price), quasi-convex in p, homogenous of degree 0 in Y and p. Given these properties, there exists Y such that V is concave in Y for Y > $\overline{Y}$. The form of Roy's identity taken from static duality theory is:

$$v^*_{hrs}(p,Y) = \frac{\frac{\partial V}{\partial p}}{\frac{\partial V}{\partial Y}} \tag{1}$$

where $v^*_{hrs}(p,Y)$ is the Marshallian optimal demand for hours worked, V is the indirect (instantaneous) utility function, Y is income, and p is price. This version of Roy's identity is appropriate, in the context of dynamic optimization, when the duality is *atemporal* (that is, relationships between instantaneous functions - see Hensher 1986) as might be assumed for independent days of the week and associated working hours. However, when we have *intertemporal* duality, interpreted here as across days of the week, the linking of instantaneous functions with the corresponding temporal functions, an inter-temporal analogue of Roy's identity is required. We can think of how individuals arrive at a decision to WFH on Friday as a consequence of having committed sufficient time to working in the main office earlier in the week. This is referred to as a consumption stream over a predefined period of time. Cooper and McLaren (1980) developed a formal proof. The essential feature of the approach is that one does not derive the hours of work equation directly from the application of Roy's identity to the instantaneous (daily) indirect utility function. Instead, one initially establishes the duality between the instantaneous indirect utility function and the *total* (throughout the week) indirect utility function (or optimal-value function) across all days of the week in a panel setting; then a 'dynamic' analogue of Roy's identity is applied which provides a derivation of Marshallian and Hicksian hours worked equations by simple differentiation of the optimal-value function.

Let u(q) be a continuous instantaneous direct utility function. Let the indirect utility function be defined by:

$$V(p,Y) = \max_q (u(q) \mid p^{'}q \leq Y) \tag{2}$$

where Y is annual income, *p* is an index representing the value of the hours worked, and *q* is the hours worked. Given V(.), the optimal-value function is the solution to (Cooper and McLaren 1980):

$$\upsilon = \upsilon(p,r,\omega,w) = \max_{Y(t)} \{\int_0^\infty (\exp(-\omega t)VY(t),p)dt \mid \int_0^\infty \exp(-rt)Y(t)dt \leq w\} \tag{3}$$

where *w* is a financial constraint, w is the time preference rate, and *r* is the nominal rate of interest. We can relax any of these assumptions such as not allowing for a time preference rate and interest rate when the period is so short, such as a typical working week.

Optimization can occur over the class of piecewise continuous functions. The Lagrangian is monotonic in the control, and thus at the optimum the constraints hold with duality. Cooper and McLaren (1980) use a control-theoretic formulation to identify the optimal paths of the state and *costate* variables and to integrate out the unobservables. Given the form of the optimal-value function, and Theorem 8 of Cooper and McLaren for mapping into v, it can be shown that the intertemporal indirect utility function is defined by equation (4).

Theorem 8, Cooper and McLaren (1980, page 608) states: Let V(.) satisfy a set of regularity conditions. Define Ψ (w, p, r, ω) $=[\omega-r]V_{ww}^{-1}V_{w}$, ϕ (w, p, r, ω) = rw - Ψ, and g(ϕ,p) =ωV− V $_{\omega}$\{rω−ϕ\}. Then over its domain of definition, g(ϕ-p) satisfies the regularity conditions with ϕ replacing *Y*.

$$v_j = \omega V(.) - \frac{\partial \dot{V}}{\partial Y^*} * [\omega - r](\frac{\partial^2 V}{\partial Y^{*2}})^{-1} \frac{\partial \dot{V}}{\partial Y^*} \tag{4}$$

and the optimal hours worked at each location by day of week (demand) equation is:

$$x_j = -\omega(\frac{\partial \dot{V}}{\partial Y^*})^{-1} \frac{\partial \dot{V}}{\partial p_j} + [\omega - r](\frac{\partial^2 V}{\partial Y^{*2}})^{-1} \frac{\partial \dot{V}}{\partial p_j} \tag{5}$$

where Y^* is household income minus the cost associated with the work location choice and hours allocated. To obtain a theoretical form for the work location indirect utility function, we adopt the general form derived from a myopic (discrete choice RUM) model with a representative utility of the form for each i^{th} discrete alternative:

$$V_i = \{\sum_{k=1}^{K}(\frac{\theta_{ki}}{\mu})b_{ki} - (\frac{\beta_i}{\mu})S_i + (\frac{\beta_i \tau_o}{\mu})C_i + (\frac{\beta_i \tau_o}{\mu})C_i Y\}\exp(-\beta_i p_i) \tag{6}$$

where b_{ki} are the k=1,…,K attributes associated with the i^{th} alternative for each day of the week (unless assumed to be generic), and S represents immediate respondent specific variables, be they socioeconomic (S) or contextual, associated with the i^{th} alternative, and C those that have to be amortized over time (which may not be applicable here except for the possibility of car ownership). If we define the total indirect utility (or optimal value) function to have the form in equation (6), then the intertemporal form of the hours worked mode; (x_j) model can be obtained by application of equation (5). The hours worked-demand model is:

$$x_i = \omega \overline{x_i} \tag{7}$$

The resulting instantaneous indirect utility function is given as equation (8).

$$v_j = \omega \overline{V_i} \tag{8}$$

which is equivalent to the myopic specification (6) other than the inclusion of the intertemporal parameter ω. We can set this intertemporal parameter to unity by reasonably assuming that the 7-day instantaneous panel is essentially atemporal. The same logic applies to hours worked. .

The Discrete Choice and Continuous Choice Model Specifications

The mixed multinomial logit (MMNL) model defines the discrete choice component. It assumes that some of the parameters are random, following a certain probability distribution. These random parameter distributions are assumed to be continuous over the sampled population. The choice probabilities of the mixed multinomial logit (MMNL) model, P_n^*, therefore now depends on the random parameters with distributions defined by the analyst. The MMNL model is summarised below in (9) (see Hensher et al. 2015).

$$\text{Prob}(choice_{ns} = j \mid \mathbf{x}_{nsj}, \mathbf{z}_n, \mathbf{v}_n) = \frac{\exp(V_{nsj})}{\sum_{j=1}^{J_{ns}} \exp(V_{nsj})} \tag{9}$$

where

V_{nsj} = $\boldsymbol{\beta}_n{}'\mathbf{x}_{nsj}$

$\boldsymbol{\beta}_n$ = $\boldsymbol{\beta} + \boldsymbol{\Delta}\mathbf{z}_n + \boldsymbol{\Gamma}\mathbf{v}_n$

$\mathbf{X}_{nsj}$ = the K attributes of alternative j in choice situation s faced by individual n,

$\mathbf{Z}_n$ = a set of M characteristics of individual n that influence the mean of the taste parameters,

$\mathbf{v}_n$ = a vector of K random variables with zero means and known (usually unit) variances and zero covariances.

The choice model embodies both observed and unobserved heterogeneity in the preference parameters of individual n. Observed heterogeneity is reflected in the term $\boldsymbol{\Delta}\mathbf{z}_n$ while the unobserved heterogeneity is embodied in $\boldsymbol{\Gamma}\mathbf{v}_n$. Structural parameters to be estimated are the constant vector, $\boldsymbol{\beta}$, the $K{\times}M$ matrix of parameters $\boldsymbol{\Delta}$ and the nonzero elements of the lower triangular Cholesky matrix, $\boldsymbol{\Gamma}$. The expected probability over the random parameter distribution can be written as

$$E\left(P_n^*\right) = \int_{\beta} P_n^*(\boldsymbol{\beta}) f(\boldsymbol{\beta}) \mid \Omega) d\boldsymbol{\beta}, \tag{10}$$

where $f(\boldsymbol{\beta} \mid \Omega)$ is the multivariate probability density function of $\boldsymbol{\beta}$, given the distributional parameters θ. By using a transformation of $\boldsymbol{\beta}$ such that the multivariate distribution becomes semi-parametric, we can write Equation (10) as

$$E\left(P_n^*\right) = \int_z P_n^*\left(\beta(z \mid \Omega)\right) \phi(z) dz, \tag{11}$$

where $\beta(z \mid \Omega)$ is a function of z with parameters Ω, and where $\phi(z)$ is the multivariate non-parametrical distribution of z. It is common to use several (independent) univariate distributions[2] instead of using a single multivariate distribution, such that Equation (11) can be written as

$$E\left(P_n^*\right) = \int_{z_1} \cdots \int_{z_K} P_n^*\left(\beta_1(z_1 \mid \theta_1), \ldots, \beta_K(z_K \mid \theta_K)\right) \phi_1(z_1) \cdots \phi_K(z_K) dz_1 \cdots dz_K. \tag{12}$$

The MMNL models used herein is estimated using a panel data set (7 days of the week per respondent) often called an 'instantaneous panel', which engenders (potential) correlation between observations common to a respondent. although the independence across respondent's assumption is maintained.

[2] Note that if one would not like to assume independent random variables, then one can sample directly from the multivariate distribution. In case of a multivariate normal distribution, this is possible through a Cholesky decomposition.

Mathematically, this means that $E\left(P_1P_2\right) \neq E(P_1)E(P_2)$, hence the log-likelihood function of the panel MMNL model may be represented as

$$\log E(L_N) = \sum_{n=1}^{N} \log E\left(\prod_{s\in S_n} \prod_{j\in J_{ns}} \left(P_{nsj}\right)^{y_{nsj}} \right), \tag{13}$$

We estimate an alternative specification leading to a utility heteroskedastic interpretation, commonly referred to as the error components (EC) model as a way to accommodate flexible substitution patterns across alternatives. Alternatives whose utility have some form of covariance share error components, which are typically distributed zero-mean random normal with a standard deviation to be estimated. As such, the estimation of error components requires that *x* takes the value 1 for the *b*[th] subset of alternatives under consideration or zero otherwise. That is, rather than associating different attributes or other such variables, EC models use a series of dummy variables to place subsets of alternatives into different 'branches' or 'nests'. An error components model form is included in the mixed logit model. The EC model becomes

$$U_{nsj} = \sum_{k=1}^{K} \beta_k x_{nsjk} \pm \sum_{l=1}^{L} \eta_l z_{lns} d_{lb}, + \varepsilon_{nsj} \tag{14}$$

where $d_{lb} = \begin{cases} 1 & \text{if } j \text{ is in nest b} \\ 0 & \text{otherwise.} \end{cases}$

The interpretation of the ECs relates to their association with specific alternatives and not with attributes as with more traditional random taste models. Each estimated EC represents the residual random error variances linking those alternatives, and by estimating different ECs for different subsets of alternatives. The variance for each alternative in nest *s* is equal to

$$Var\left(U_{nsj}\right) = E\left(\eta_j z_{nsj} d_{bj} + \varepsilon_{nsj}\right)^2 = \vartheta_b + \pi^2/6\sigma_n^2. \tag{15}$$

After estimation of the mixed logit model with error components, we obtain the choice probabilities that are the basis of the selectivity correction (SC) variable that is used to account for the potential correlation between the unobserved components of the discrete and continuous choices and the determination of a method for handling the endogeneity of the unobserved attributes of the continuous choice model, the latter being working hours associated with each alternative. There is a large literature on ways to construct selectivity correction indicators and we have chosen one developed by Hay (1980) and implemented by Dubin (1982) and Dubin and McFadden (1984). Full details are given in Hensher and Milthorpe (1987), with the selectivity correction formula used given in (16).

$$E(\eta \mid \delta_i = 1) = (\frac{6}{\pi^2})\rho_i \sigma (\frac{J-1}{J}(Log P_i) + \sum_{j=1 j\neq i}^{J} (\frac{Log P_j}{J})(\frac{P_j}{1-P_j})) \tag{16}$$

where the coefficient of the selectivity correction variable is $(\frac{6}{\pi^2})\rho_i \sigma$ where σ is the standard error of the estimate and ρ_i is the correlation between the error terms of the discrete and continuous choices. Given the estimated parameter for selectivity correction, ρ_i can be obtained.

This selectivity correction variable is unique to each discrete choice alternative.

The continuous choice model that is aligned with the alternatives in the discrete choice model is specified as a seemingly unrelated regression equation (SURE) model. We have combined the peak and off-peak alternatives for the main office only and for the two blended alternatives since the distinction between peak and off-peak hours working is not relevant for SURE given the distinction was to recognize whether the commuting trip occurred in a peak or off-peak period. The SURE model is given as equation system (17).

$$\begin{aligned}
\mathbf{y}_1 &= \mathbf{X}_1\mathbf{b}_1 + \mathbf{e}_1,\\
\mathbf{y}_2 &= \mathbf{X}_2\mathbf{b}_2 + \mathbf{e}_2,\\
&\dots\\
\mathbf{y}_M &= \mathbf{X}_M\mathbf{be}_M + \mathbf{e}_M.\\
E[\mathbf{e}_i/\mathbf{X}_1,\dots] &= \mathbf{0},\\
E[[\mathbf{e}_i\,\mathbf{e}_i\,|\mathbf{X}_1,\dots] &= \sigma_{ij}\mathbf{I}.
\end{aligned} \tag{17}$$

The disturbances across equations are allowed to be freely correlated. Collecting the M disturbances for a particular observation in a column vector $\mathbf{e}_t = [e_{t1}, e_{t2}, \dots e_{tM}]'$, the model specifies $E[\mathbf{e}_t|\mathbf{X}_1,\dots] = \mathbf{0}$, $E[\mathbf{e}_t\,\mathbf{e}_t'\,|\mathbf{X}_1,\dots] = \sum$.

Data source

The data is obtained from the March 20124 Transport Opinion Survey (TOPS)[3], a biannual survey of adults aged 18 and over across Australia launched in March 2010. The sample is representative of Australia's population distribution and demographic characteristics. The March 2024 survey was conducted between the 1st and 10th of March 2024 with 1,030 completed responses[4]. Table 2 summarises the profile of the data with quotas imposed by State, location, gender, and age in line with the latest census.

Table 1. A summary of the Quota sampled survey respondents

State:	**N**	**%**
NSW	342	33.2%
VIC	253	24.6%
QLD	203	19.7%
SA	89	8.6%
WA	113	11.0%
TAS	12	1.2%
NT	6	0.6%
ACT	12	1.2%
Location:	**N**	**%**
State capital city	664	64.5%
Regional city	209	20.3%
Town or village	106	10.3%
Country, rural or remote area	51	5.0%
Gender:	**N**	**%**
Male	506	49.13%
Female	523	50.78%
Other	1	0.10%

[3] https://sydney.edu.au/business/our-research/institute-of-transport-and-logistics-studies/transport-opinion-survey.html

Age group:	N	%
18 to 34 years	314	30.5%
35 to 54 years	374	36.3%
55 years and over	342	33.2%

Descriptive Profile of Key Evidence

In the March 2024 survey, we asked about work patterns in a typical working week, identifying the number of hours for each day of the week (DoW) and time of the day (ToD) associated with various working locations, working hours, commuting time, and hybrid work. We defined working people as people who did paid work in the last two weeks.

Among all capital cities, the percentage of WFH time is the highest in Melbourne (31.6%), followed by Sydney (23.2%) and Brisbane (20.7%) (Figure 3). The percentages of WFH hours are below 20% in Adelaide, Perth, and other capital cities. The overall incidence of WFH for all capital cities is close to 23%. Melbourne ranked first with the highest number of working days WFH (1.03 days per week), followed by Sydney (0.93 days per week) and Brisbane (0.82 days per week).

The pattern of how people arrange their work hours is similar from Monday to Friday in the capital cities data (see Figure 2). However, a more apparent pattern can be observed in the GSMA data (Figure 3), which shows how people arrange their work time. At the beginning and the end of the week, we can observe a slightly higher number of people working from home only, with Friday at 28% and Monday at 25%. In contrast, mid-weekdays, including Wednesday (68%), Tuesday (67%) and Thursday (65%), have the highest levels of people working from the main workplace only. Monday (13%) and Tuesday (12%) are the days with more people working hybrid at both places.

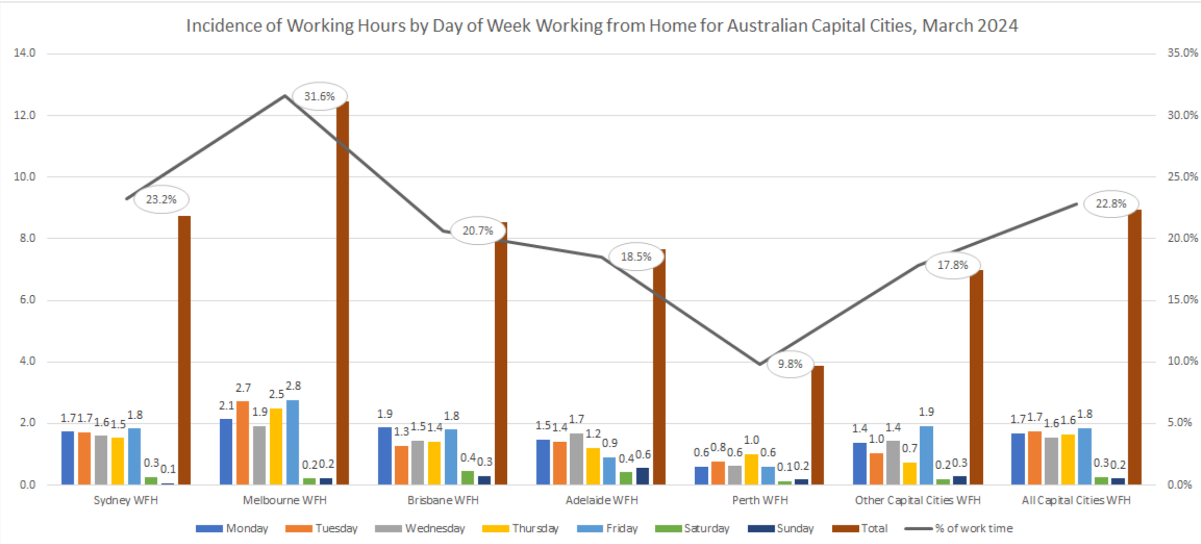


Figure 2. Incidence of WFH hours by Day of week for each Capital City

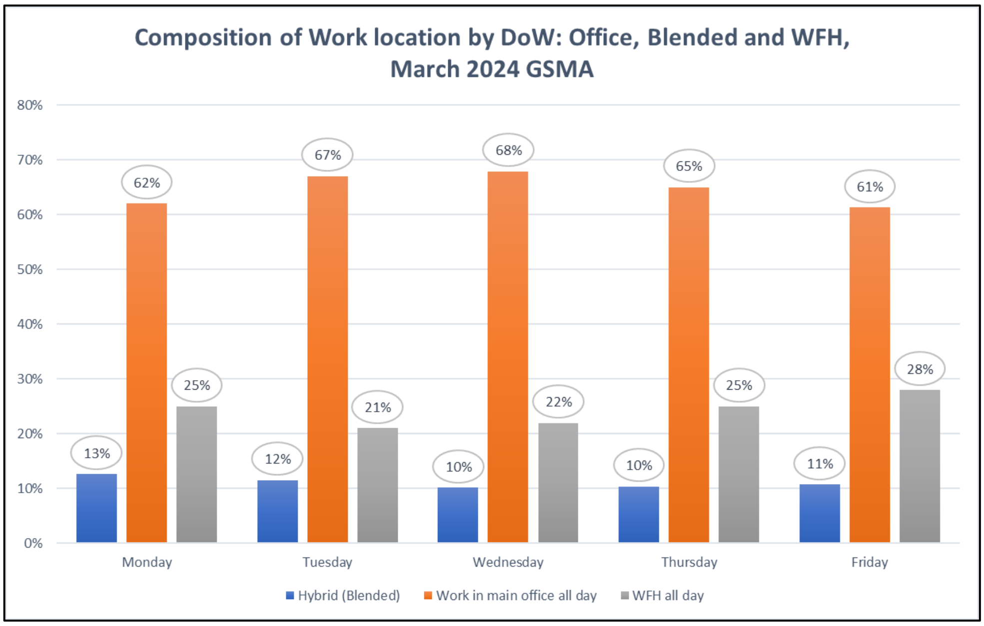


Figure 3. Composition of work by location for each Day of the Week for the GSMA

The pattern is less evident in the nationwide data, as shown in Figure 4. However, the proportion of WFH-only individuals is still at the highest on Friday (28%), and the proportion of people working at the main offices only is also at the highest on a Wednesday (64%).

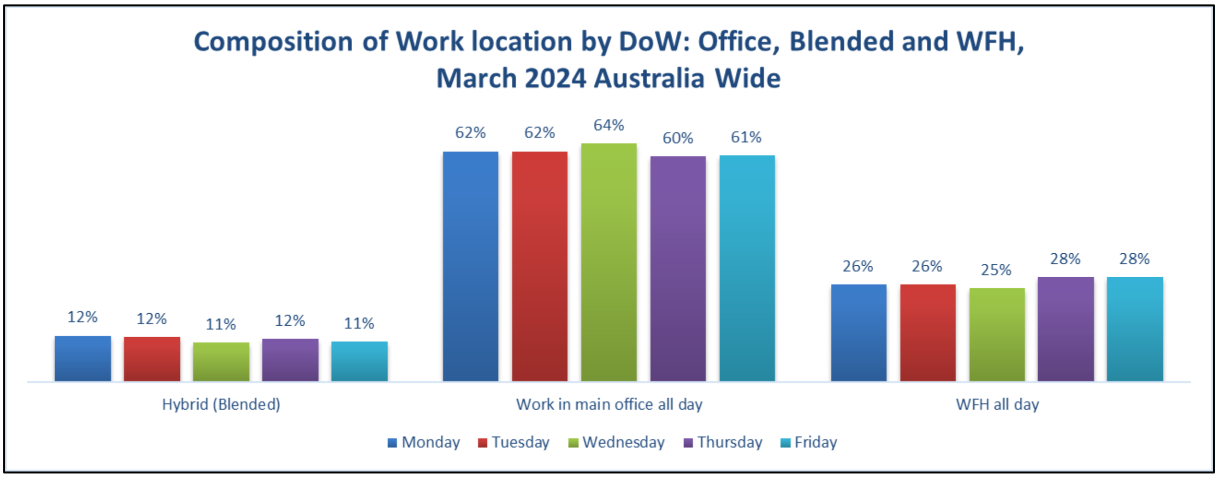


Figure 4. Composition of work by location for each Day of the Week, Australia

Workers commute to the workplace at different times throughout the week (Figure 5 Australia wide and Figure 1 for the GSMA). Tuesday sees the highest proportion of people leaving home during peak hours, either in the morning or afternoon peaks (i.e., afternoon peak for working the night shift). Monday, Wednesday, and Friday appear similar regarding peak hour commuting between 52% to 54%. Thursday is the only weekday that more people commute during off-peak hours than peak hours (51% vs. 49%). There appears to be a noticeable switch out of peak periods to off peak periods for commuting.

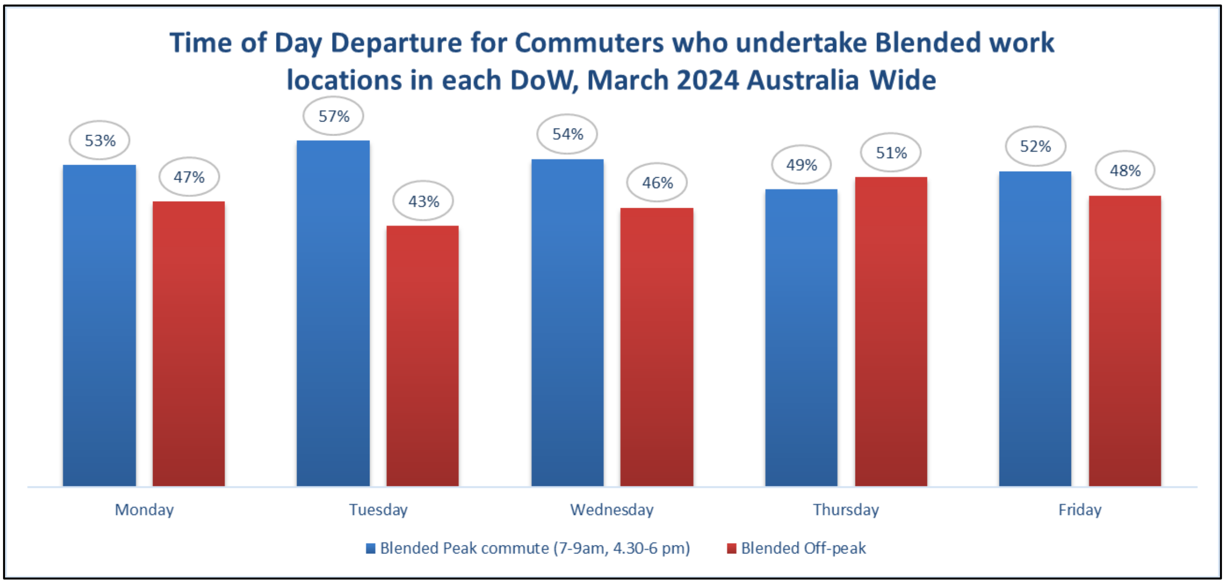


Figure 5. Time of day commuting for each Day of the Week, Australia

Driving any petrol/diesel/hybrid vehicle is the most dominant mode of transport for commuting, at 61.8% (Figure 6). Taking public transport is also popular, with taking train at 16.7%, bus at 7.2%, and light rail and ferry at 2.4% combined. Driving an electric vehicle for commuting has a small share at 1.2%. Active modes of transport are the choices for a small proportion of commuters, with walking at 6.7%, cycling at 0.9% and using E-bike/E-scooter at 0.6%. Taxi use, rideshare, and car share for commuting have a combined mode share of 1.2%, reflecting the current market penetration of fuel-efficient vehicles in Australia. Using private vehicles as a passenger has a small share of 0.9%. Driving motorbikes or mopeds is the choice for 0.3% of commuters.

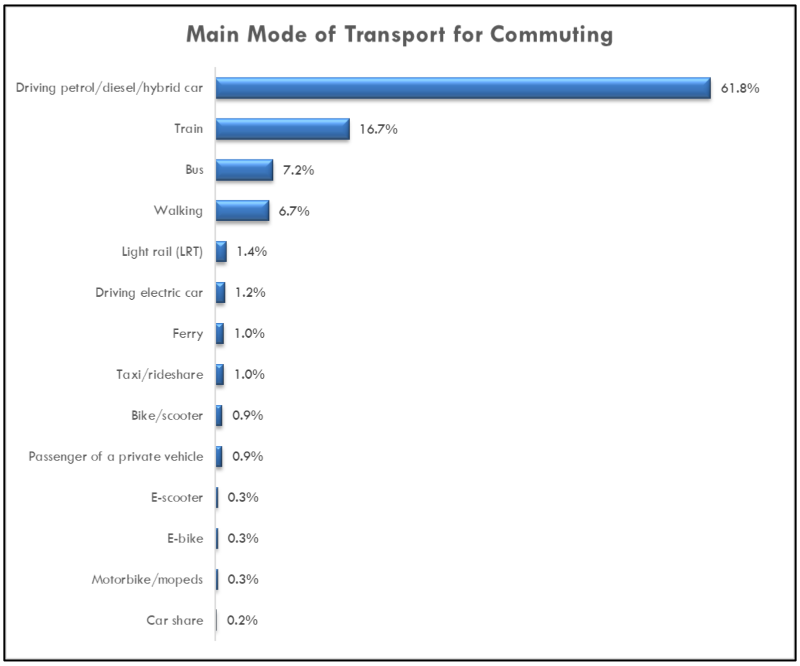


Figure 6. Commuting mode, Australia

Model Estimation Results

The final MMNL model with error component variance estimates is summarised in Table 2, estimated as a panel specification (equation 13) using 500 Halton intelligent draws. The overall goodness of fit aligns with the typical statistical performance of disaggregated discrete choice model (in the range 0 .2-0.4; Hensher et al. 2015). The mean probability estimate associated with working at various locations for each day of the week is summarised in Figure 8. The growing interest in blended workdays is highlighted as the incidence of all three work location alternatives during the five workdays is very similar. The available data items are listed in the Appendix.

Two random parameters were identified for the WFH alternative. Professionals are more likely to WFH than other occupations and those who have a longer commute are more likely to have higher probability of WFH, both of which conform with evidence from other studies, notably that the longer the commute (be it distance or travel time), the higher the probability of WFH all day. In addition to these two random parameters, we found that clerical and admin workers have a higher probability of working from home on any given day, and also of great interest is that the probability of WFH is higher for residents of Victoria and lower for residents of Western Australia for reasons we are aware of given significant lockdowns during COVID in Victoria and border closures in WA during Covid.

When an individual works in the main office and commutes in the peak or off-peak periods, those aged between 18 and 55 have a higher probability of working in the main office only; however, the probability of working in main office is lower on a Friday regardless of what time of day an individual commutes. Commuters travelling to the main office during peak period hours have a higher probability of using public transport compared to any other mode.

For days when individuals choose a hybrid or blended work location alternative and commute in the peak period, they have a lower probability of doing so on a Friday, and when they do undertake blended work location activity, they have a higher probability of not driving to the office by car compared to using other modes. Male workers tend to have a higher probability than other genders to undertake blended office location work and travel during the off peak. As expected, there is a higher probability associated with not working on a Saturday or Sunday.

The three error component parameter estimates show clearly statistically significant unobserved variances between the alternatives with the greatest variance being associated with the hybrid work location alternatives. This suggests that there are potentially more sources of influence on choosing the hybrid location alternative compared to being only in the main office or WFH on any given day.

Table 2. Mixed Multinomial Logit Model with Error Components

Random Parameters: Mean	*Alternative*	*Parameter estimate*	*t-value*
Professional occupation (1,0)	WFH only	1.0369	11.0
Time saved by not commuting (mins)	WFH only	0.0080	2.0
Random Parameters: Standard deviation			
Professional occupation (1,0)	WFH only	1.0369	11.0
Time saved by not commuting (mins)	WFH only	0.0040	2.0
Non-Random parameters:			
Peak main office constant	Main Office peak	0.3409	3.07
Age 18 o 34 years (1,0)	Main Office peak	0.5943	4.51
Age 35 to 55 years (1,0)	Main Office peak	0.6672	5.02
Friday dummy variable (1,0)	Main Office peak	-0.3422	-2.26

Commute by public transport (1,0)	Main Office peak	0.1608	2.93
Off-peak main office constant	Main Office off-peak	0.2593	2.38
Age 18 o 34 years (1,0)	Main Office off-peak	0.5266	4.06
Age 35 to 55 years (1,0)	Main Office off-peak	0.6824	5.22
Friday dummy variable (1,0)	Main Office off-peak	-0.3087	-1.97
Peak hybrid work location constant	Hybrid location peak	-2.8699	-11.5
Friday dummy variable (1,0)	Hybrid location peak	-0.4166	-1.97
Commute by car as driver (1,0)	Hybrid location peak	-0.6066	5.56
Off-peak hybrid work location constant	Hybrid location off-peak	-3.3602	-12.9
Male (1.0)	Hybrid location off-peak	0.4262	4.09
Work from Home constant	WFH only	-1.5556	-7.93
Live in Victoria (1,0)	WFH only	0.7274	4.13
Live in Western Australia (1,0)	WFH only	-1.2542	-4.43
Clerical and Admin occupation (1,0)	WFH only	0.9209	4.58
Saturday dummy variable (1,0)	No work all day	3.9332	22.1
Sunday dummy variable (1,00	No work all day	4.3301	33.2
Error components:			
Main Office -peak and off-peak		-1.2268	-19.9
Hybrid main office and other location peak and off-peak		4.0119	20.3
Work from home only		2.8491	23.4
AIC/N	2.337		
Log-likelihood at zero	-8604.03		
Log-likelihood at convergence	-5585.73		
McFadden Pseudo R^2	0.351		
Number of observations	4802		
Panel data groups	686		

Figure 7 shows the mean probability distribution across each work location alternative for each day of the week, noting similarities across all weekdays, and Figure 8 shows the distribution of the probability associated with a particular location alternative across the days of the week. We see, for example, that the probability of working only in the main office is similar throughout Monday to Thursday but lower on Friday, with WFH only and blended work locations having a higher probability on Friday.

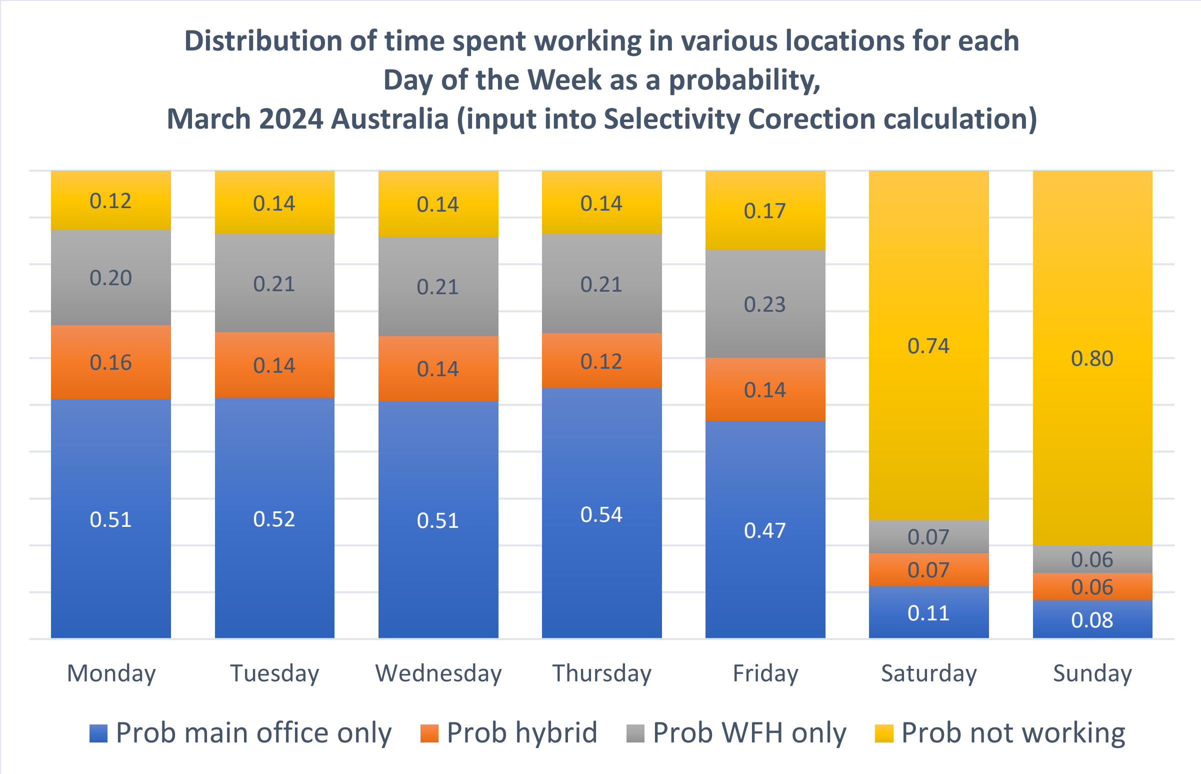


Figure 7. Probability of working at various locations for each day of the week

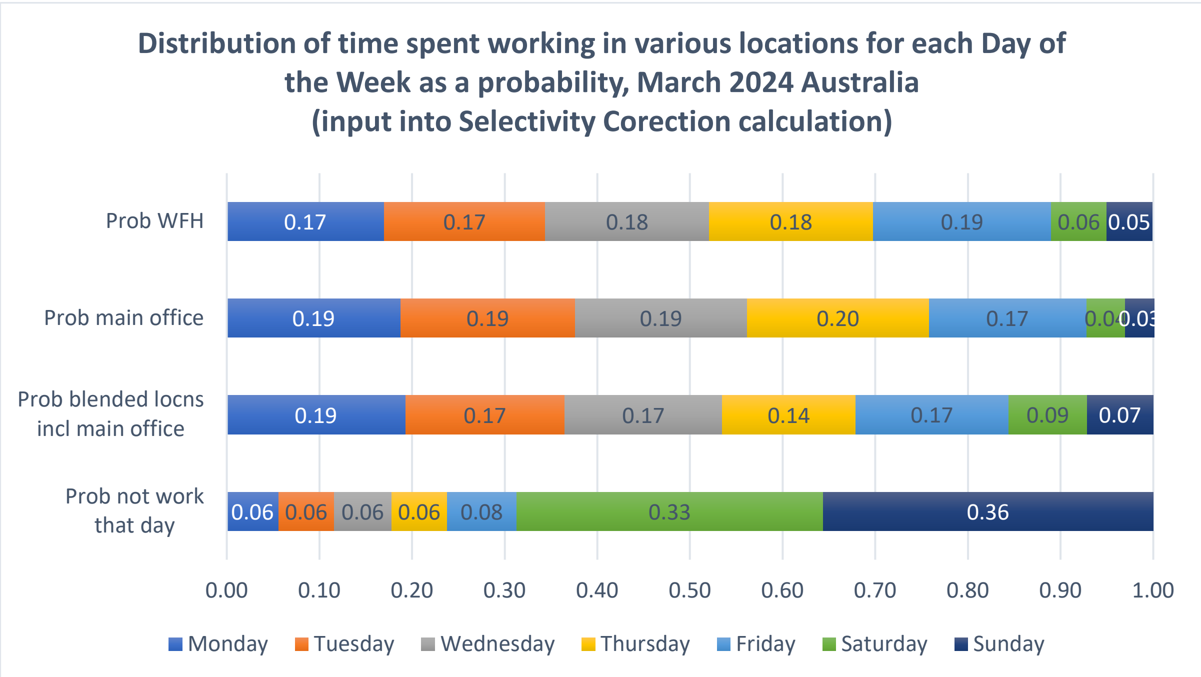


Figure 8. Probability distribution for each work location alterative foreach day of the week.

The parameter estimates associated with the discrete choice model are behaviourally of limited interest given the non-linear format of the model. To obtain behaviourally informative evidence, we present direct and cross elasticities of all statistically significant influences associated with the various probabilities of work location (Table 3). The direct elasticities (bolded) are of the opposite sign to the cross elasticities, all of which are probability weighted across the sample in contrast to a naïve aggregation approach. All elasticity estimates are relatively inelastic, and statistically significant.[5] An arc elasticity formula is applied in calculating the elasticity estimates for the dummy variables, which are all variables except for the commuting travel time. Age, professional occupation, commuting by car, and commuting time saved (as a proxy for 'distance' from home to the main office) have the highest relative inelasticity. For example, a 10% increase in the commuting time results in a 1.71% increase in the probability of WFH only, *ceteris paribus*, and a commuter aged between 35 to 55 years has a 0.271 higher probability of going to the main office in the off-peak compared to commuters in the other age groups, *ceteris paribus*. A commuter who travels to work by car compared to another mode has a 0.309 higher probability of not undertaking work in blended work locations relative to using other modes.

Table 3. Mean Direct and Cross-Elasticities associated with the MMNL model

Influence	Main Office peak	Main Office off-peak	Hybrid location peak	Hybrid location off-peak	WFH only	Not work all day
Professional occupation (1,0)	-0.038	-0.036	-0.026	-0.025	**0.156**	-0.2028
Commuting time (mins)	-0.048	-0.046	-0.032	-0.029	**0.171**	-0.022
Age 18 o 34 years (1,0)	**0.177**	-0.099	-0.026	-0.026	-0.032	-0.032
Age 35 to 55 years (1,0)	**0.245**	-0.144	-0.035	-0.034	-0.042	0.041
Friday (1,0)	**-0.035**	0.199	0.006	0.006	0.007	0.006
Commute by public transport (1,0)	**0.028**	-0.015	-0.005	-0.003	-0.006	-0.005
Age 18 o 34 years (1,0)	-0.079	**0.168**	-0.020	-0.019	-0.024	0.024
Age 35 to 55 years (1,0)	-0.129	**0.271**	-0.032	-0.032	-.038	-0.037
Friday (1,0)	0.016	**-0.034**	0.005	0.005	0.006	0.005
Friday (1,0)	0.002	0.002	**-0.046**	0.019	0.002	0.001
Commute by car as driver (1,0)	0.011	0.012	**-0.309**	0.139	0.009	0011
Male (1.0)	-0.008	-0.008	-0.084	**0.169**	-0.006	0.007
Victoria (1,0)	-0.013	-.0.013	-0.008	-0.008	**0.052**	-0.009
Western Australia (1,0)	0.009	0.009	0.005	0.005	**-0.034**	0.006
Clerical and Admin occupation (1,0)	-0.022	-0.022	-0.016	-0.013	**0.090**	-0.016

The choice probabilities from the MMNL model are used to calculate the selectivity correction associated with each alternative, using equation (15). The respective SC estimates, mean and standard deviation, associated with each of the alternatives are as follows, noting that we combined the peak and off-peak probabilities since with a focus on hours worked at each location made no sense to separate the peak and off-peak given that distinction relates only to the time of day that the commuting trip commenced: Main office SC =-1.237 (0.612), Hybrid work location SC =-2.165 (0.403), WFH only SC = -1.931 (0.591), and no work SC = -1.519 (0.727).

[5] Confidence limits are available on request. The Krinsky and Robb method is used to obtain standard errors of estimates and confidence intervals.

In estimating the SURE system of equations, we ensured that the data for the hours worked in the main office only, WFH only, and the hybrid locations defined as the main office and any other location, were aligned exactly with the definitions in the discrete choice set of alternatives. The average number of hours and standard deviation worked per day associated with each alternative across all days of the week are as follows: Main office = 3.20 (3.89), Hybrid work location =0.357 (1.72), WFH only = 1.171 (2.74), and no work SC = -1.519 (0.727). This is an average for the entire week of 33 hours (or an average of 4.73 hours per day based on a 7-day week).

The final SURE models with and without selectivity correction are given in Table 4, estimated by generalised least squares regression. The selectivity correction parameters are found to be statistically significant when location and hours worked are jointly observed in the data set, and hence accounting for the presence of error correlation between the discrete and continuous choice models is justified. To gain a greater appreciation of the impact of including or excluding the selectivity correction, we have calculated, in Figure 9, the percentage difference of the mean direct elasticities in the presence of selectivity correction and no allowance for selectivity correction for the hours allocated per day of the week to the main office only, working for home only, and hybrid or blended work location on the day. Excluding the expected differences for the constants, we see a few sizeable behavioural response differences, notably for the Wednesday dummy variable for the main office, the commuting time for WFH, and the Friday dummy variable for WFH. There are other small but non-marginal differences, and combined, the elasticity adjustments are clearly an important indication of the bias in the mean associated with ignoring selectivity correction when there is evidence of error correlation between the indirect utility expressions associated with the discrete choice model and the demand equations defining the set of continuous choices.

Table 4. SURE models with and without Selectivity Correction

Influence	Location	With Selectivity Correction		Without Selectivity Correction	
	Alternative	*Parameter estimate*	*t-value*	*Parameter estimate*	*t-value*
Constant	Main Office	4.9057	37.4	1.8739	23.4
Town (1,0)	Main Office	-0.5887	-4.09	-0.5661	-3.61
Male (1,0)	Main Office	0.5490	5.88	0.5888	6.03
Wednesday (1,0)	Main Office	0.2008	1.98	1.0915	8.55
Commute in peak (1,0)	Main Office	2.3454	22.9	3.3204	31.6
Constant	Hybrid Location	0.8393	5.91	0.4238	7.00
Commute in peak (1,0)	Hybrid Location	0.2221	3.91	0.2793	5.05
Professional occupation (1,0)	Hybrid Location	-0.2494	-4.19	-0.2890	-4.83
Management occupation (1,0)	Hybrid Location	-0.1872	-2.62	-0.1971	-2.75
Clerical and admin (1,0)	Hybrid Location	-0.1713	-2.42	-0.2101	-2.94
Female (1,0)	Hybrid Location	-0.1862	-3.67	-0.1956	-3.87
Car driver commute (1,0)	Hybrid Location	0.1879	3.66	0.1686	3.27
Constant	WFH only	0.6420	2.58	-0.8087	-5.45
Commuting time (mins)	WFH only	0.0270	11.12	0.0360	16.3
Professional occupation (1,0)	WFH only	0.4370	4.58	0.6280	6.80
Management occupation (1,0)	WFH only	0.6395	6.02	0.6118	5.52
Clerical and admin (1,0)	WFH only	0.4883	4.47	0.6336	5.76
Car driver commute (1,0)	WFH only	0.4226	3.48	0.4389	3.45
Victoria (1,0)	WFH only	0.2817	3.30	0.4576	5.40
Age 35 to 54 years (1,0)	WFH only	0.2668	3.76	0.3012	4.07

Female (1,0)	WFH only	0.1371	1.97	0.1728	2.16
Friday (1,0)	WFH only	0.1657	1.92	0.5569	5.29
Commute by public transport (1,0)	WFH only	0.3875	2.88	0.3814	2.70
Constant	No work	0.0083	3.19	0.0072	5.95
Clerical and admin (1,0)	No work	-0.0078	-2.65	-0.076	-2.70
Selectivity correction	Main Office	2.1122	27.5		
Selectivity correction	Hybrid Location	0.2029	3.30		
Selectivity correction	WFH only	0.5364	6.71		
Selectivity correction	No work	0.0007	0.45		
Log-likelihood		-26831.9		-27405.2	

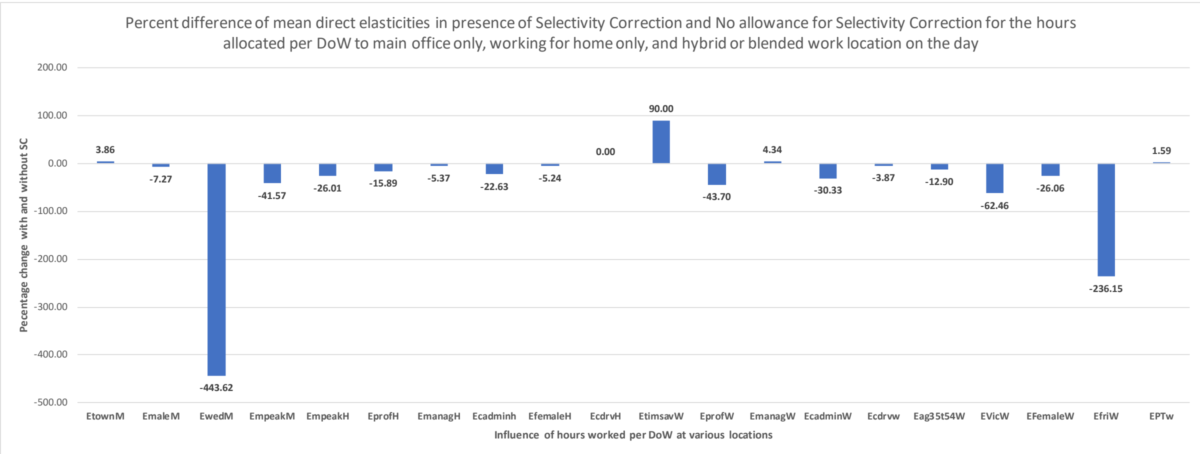


Figure 9. The percentage difference in elasticity impacts of including and excluding the selectivity correction variable.

The mean direct elasticities associated with the explanatory variables influencing each of the work location hours models are given in Figures 10-12 for the main office, the hybrid work location, and WFH only. We present the results in the presence and absence of selectivity correction. As a general observation, when we allow for selectivity correction, we suppress the mean direct elasticity for the relationship between a particular influence and the quantum of hours when an individua WFH all day, at the main office or in a blended location environment. We have not included the time saved commuting variable since SC has no influence on the mean direct estimate.

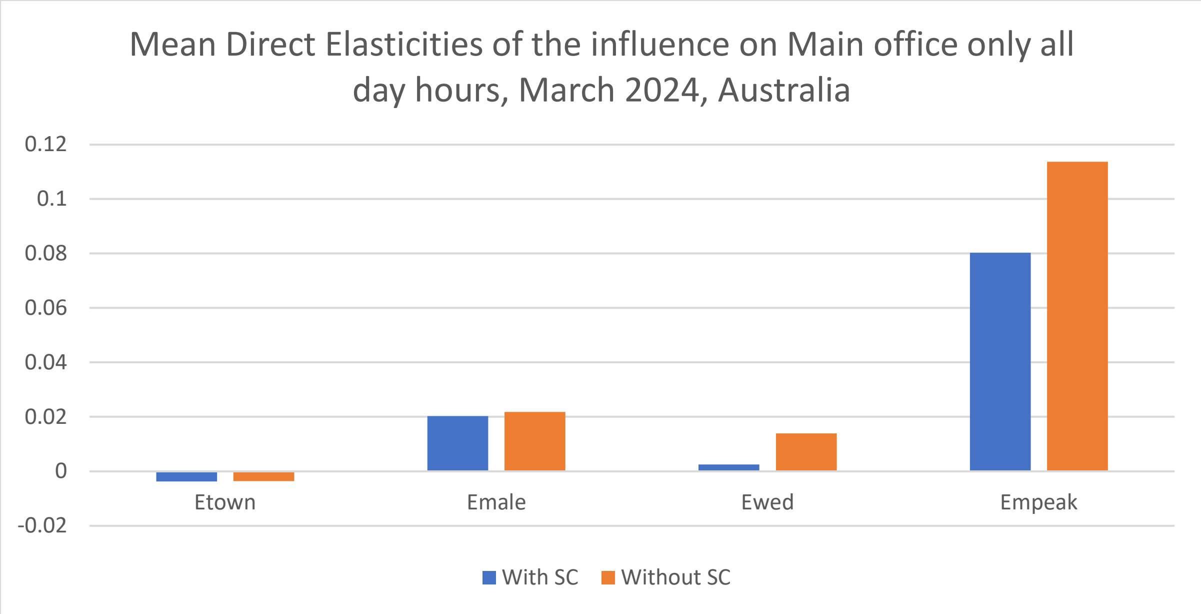


Figure 10. Mean direct elasticities for the hours working at the main office.

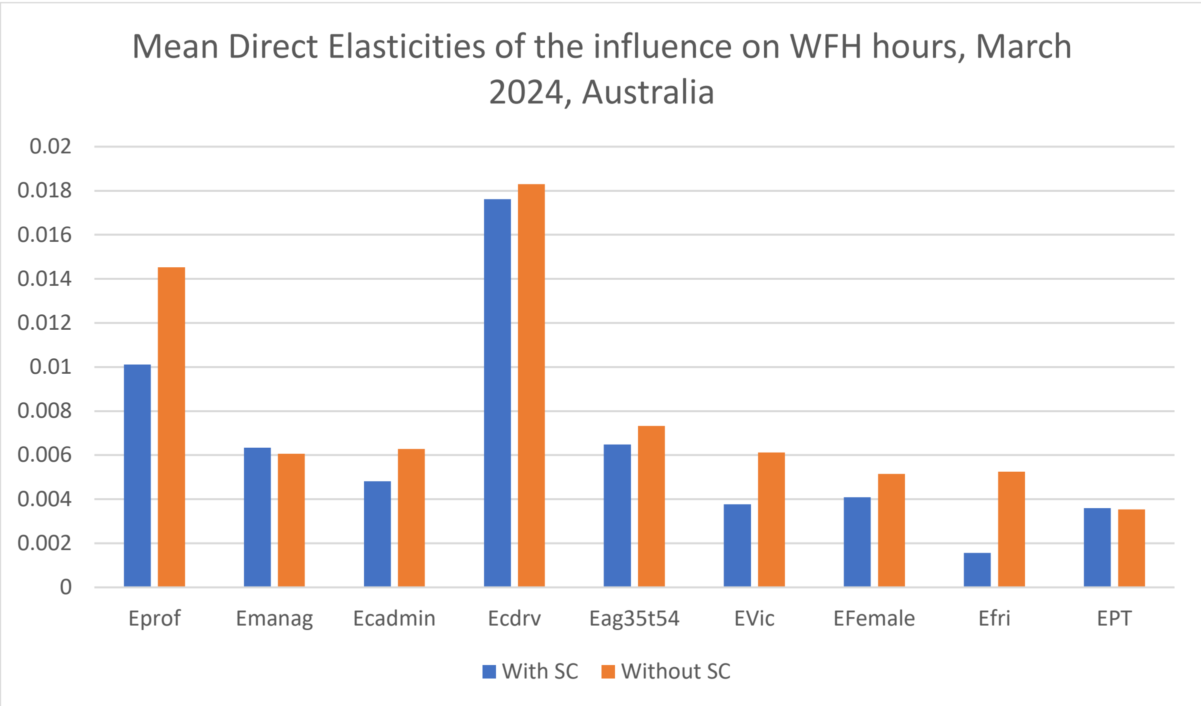


Figure 11. Mean direct elasticities for the hours working only at home.

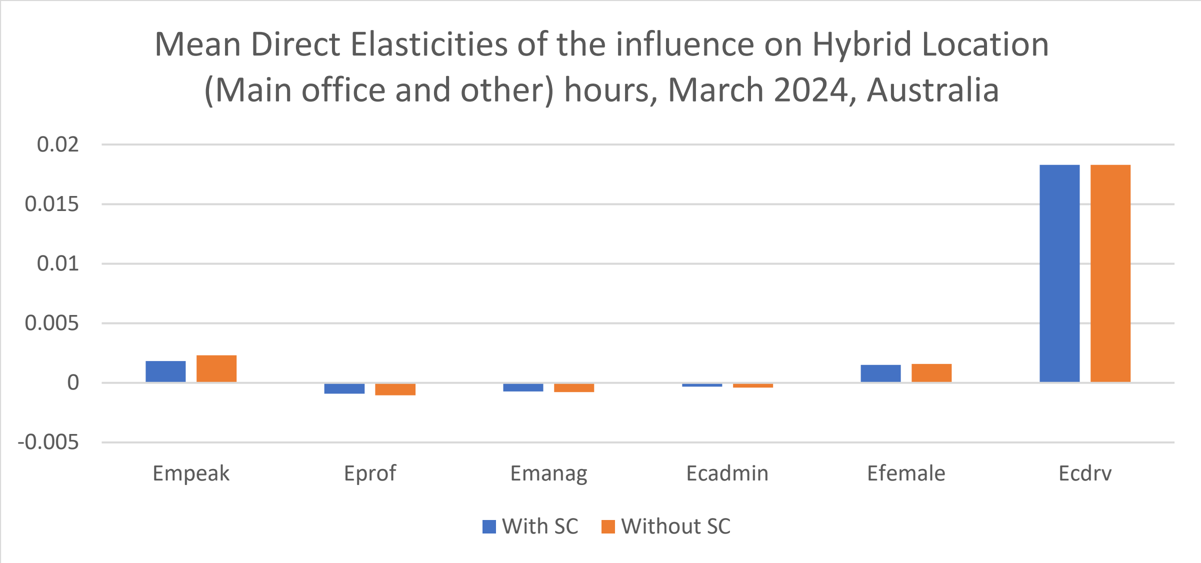
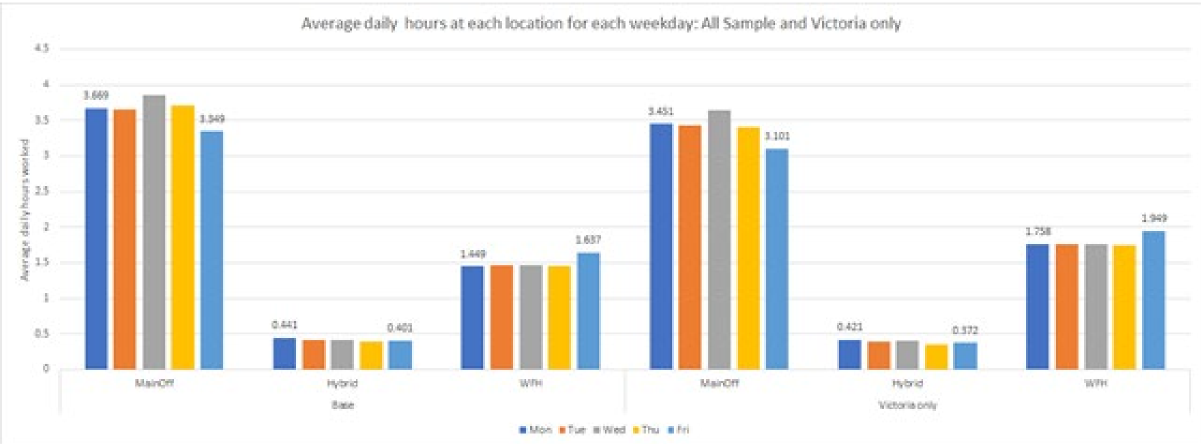


Figure 12. Mean direct elasticities for the hours working at the main office and at another location.

Figure 13 (including the accompanying Table) shows the average working hours associated with the application of SURE model equations for each of the work location alternatives for each weekday. As expected, Friday has a lower average number of hours worked in the main office compared to the other weekdays and a higher quantum of hours work at home; however, for the blended locations, Monday exhibits the highest number of hours on average. We can run many scenarios to identify how sensitive the mean estimates are to different levels of the explanatory variables. We have selected as an example, a comparison of the base for the entire sample, and for only workers who live in Victoria. As expected, given the history of lockdown and greater preference to WFH in Victoria during the COVID-19 pandemic, this is reinforced through the SURE model application as we come out of Covid-19. The difference is very stark.



	Base			Victoria only			Percent difference (Vic vs base)		
	MainOff	Hybrid	WFH	MainOff	Hybrid	WFH	MainOff	Hybrid	WFH
Mon	3.669	0.441	1.449	3.451	0.421	1.758	-5.94%	-4.54%	21.33%
Tue	3.656	0.418	1.463	3.435	0.387	1.757	-6.04%	-7.42%	20.10%
Wed	3.853	0.419	1.463	3.637	0.401	1.757	-5.61%	-4.30%	20.10%
Thu	3.714	0.387	1.448	3.405	0.355	1.747	-8.32%	-8.27%	20.65%
Fri	3.349	0.401	1.637	3.101	0.372	1.949	-7.41%	-7.23%	19.06%

Figure 13. Average daily hours worked at each location for each day of the week for all sample and Victoria only

Conclusions

This paper has integrated two behaviourally important changes in the nature of work, namely where it is undertaken, and the quantity of hours allocated to each work location. The location and allocation of hours varies by day of the week with a notable increase in working from home only on a Friday, suggesting that we should be cautious in using an average day of the 5-day week as the basis of predicting commuting patterns throughout the week. In addition, some work activity has moved to the weekend days as a result of increased flexibility in the working task, devoid of any stigma that may have prevailed pre-COVID-19.

In recognising the interdependence between the discrete choice amongst locations of work and the continuous choice of hours working at each location, a discrete-continuous choice model framework is implemented. With the possibility that some unobserved influences on the choice amongst work locations for each day of the week may be correlated with unobserved influences on the hours allocated to each location for each day of the week, we invoke a selectivity correction index as a way of testing for error correlation between these two choice models. Error correlation is shown to be present, and failure to correct for it tends to have a behaviourally suppressing effect on the role that each explanatory variable plays in influencing the amount of time allocated to each work location throughout the week. This can in turn affect the reliability of the policy evaluation measures that the analyst can draw post estimation.

The model system proposed is appealing in that it can be integrated easily into a strategic transport model system in order to adjust commuting travel activity by mode and time of day in the presence of a more flexible and hence less rigid profiling of when and where work takes place. This has profound implications on the transport network in respect of time-of-day movement and even the changing location of work, especially at the main office, notably in higher density locations where occupations such as professionals, managers, clerical and admin staff dominate such as central business districts (see Hensher et al. 2023).

The growing support for WFH and blended work arrangements that facilitate reduced peaking of commuting activity is not going away and has been shown in many studies including the current one to be an important change in the way we live and work. We have suggested in previous papers that the increase in WFH and blended daily work locations has become a positive unintended consequence of COVID-19 and possibly one of the most powerful policy levers that we now have in the transport and land use planner's toolkit to effect change that can deliver on sustainability aspirations.

CRediT authorship contribution statement

David A. Hensher: Conceptualization, Data curation, Formal analysis, Methodology, Software; Writing – original draft, Writing – review & editing.
Edward Wei: Data curation, Writing – review & editing.
Andrea Pelligrini: Conceptualization; Writing – review & editing.

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Appendix. Descriptive Profile of data items

Variable Definitions	Unit	Acronym	Mean	SD	Cases
In the Great Sydney Metropolitan Area (GSMA)	Dummy (1/0)	GSMA	0.30	0.46	4802
In capital cities	Dummy (1/0)	CAPITAL	0.68	0.47	4802
In regional cities	Dummy (1/0)	REGCITY	0.19	0.39	4802
In regional towns	Dummy (1/0)	TOWN	0.09	0.28	4802
In remote regional areas	Dummy (1/0)	REMOTE	0.04	0.19	4802
Manager	Dummy (1/0)	MANAG	0.17	0.38	4802
Professional	Dummy (1/0)	PROF	0.33	0.47	4802
Technicians and trades	Dummy (1/0)	TECH	0.06	0.24	4802
Community and personal services	Dummy (1/0)	COMUWORK	0.07	0.26	4802
Clerical and administration	Dummy (1/0)	CLEADMIN	0.19	0.39	4802
Sales	Dummy (1/0)	SALES	0.08	0.27	4802
Machine operators / drivers	Dummy (1/0)	MACHINE	0.02	0.15	4802
Labourer	Dummy (1/0)	LABOUR	0.07	0.26	4802
looking for job	Dummy (1/0)	UNEMP	0.00	0.07	4802
not in the workforce	Dummy (1/0)	NOTWORK	0.01	0.08	4802
New South Wales	Dummy (1/0)	NSW	0.35	0.48	4802
Victoria	Dummy (1/0)	VIC	0.25	0.43	4802
Queensland	Dummy (1/0)	QLD	0.19	0.39	4802
South Australia	Dummy (1/0)	SA	0.08	0.27	4802
Western Australia	Dummy (1/0)	WA	0.10	0.30	4802
Tasmania	Dummy (1/0)	TAS	0.01	0.10	4802
Northern Territory	Dummy (1/0)	NT	0.01	0.09	4802
Australian Capital Territory	Dummy (1/0)	ACT	0.02	0.13	4802
Male	Dummy (1/0)	MALE	0.53	0.50	4802
Female	Dummy (1/0)	FEMALE	0.47	0.50	4802
Age 18 to 34	Dummy (1/0)	AG18T34	0.37	0.48	4802
Age 35 to 54	Dummy (1/0)	AG35T54	0.44	0.50	4802
Age 55 or over	Dummy (1/0)	AG55OVER	0.19	0.39	4802
Main commuting mode- drive ICE car	Dummy (1/0)	DRIVEICE	0.52	0.50	4802
Main commuting mode- drive EV	Dummy (1/0)	DRIVEEV	0.01	0.10	4802
Main commuting mode- passenger	Dummy (1/0)	PASSGER	0.01	0.09	4802
Main commuting mode- motorbike	Dummy (1/0)	MOTORBIK	0.00	0.05	4802
Main commuting mode- taxi or rideshare	Dummy (1/0)	TAXIRDSH	0.01	0.09	4802
Main commuting mode- car share	Dummy (1/0)	CARSH	0.00	0.04	4802
Main commuting mode- bus	Dummy (1/0)	BUS	0.06	0.24	4802
Main commuting mode- train	Dummy (1/0)	TRAIN	0.14	0.35	4802
Main commuting mode- ferry	Dummy (1/0)	FERRY	0.01	0.09	4802
Main commuting mode- light rail	Dummy (1/0)	LTRAIL	0.01	0.11	4802
Main commuting mode- walking	Dummy (1/0)	WALK	0.06	0.23	4802
Main commuting mode- bike and scooter	Dummy (1/0)	BIKESCOT	0.01	0.09	4802
Main commuting mode- E-Bike	Dummy (1/0)	EBIKE	0.00	0.05	4802
Main commuting mode- e-scooter	Dummy (1/0)	ESCOOT	0.00	0.05	4802
Hours working in the main office on a day	hours	MAINOFHR	3.89	4.02	4802
Hours working at home	hours	WFHHR	1.17	2.74	4802
Hours working at other locations	hours	OTHERHR	0.36	1.72	4802
Home to work commuting time	mins	HTOWMIN	16.31	23.41	4623
Work to home commuting time	mins	WTOHTIME	16.25	22.49	4623
Two-way commuting time	mins	TWOWTIME	32.56	45.20	4623

Time saved if not commuting	mins	TIMESAVE	21.22	17.10	4802
Leaving home to work during morning peak (7 to 9 am)	Dummy (1/0)	MPEAK	0.28	0.45	4802
Leaving home to work during afternoon peak (4:30 to 6 pm)	Dummy (1/0)	EPEAK	0.01	0.09	4802
Monday	Dummy (1/0)	MON	0.14	0.35	4802
Tuesday	Dummy (1/0)	TUE	0.14	0.35	4802
Wednesday	Dummy (1/0)	WED	0.14	0.35	4802
Thursday	Dummy (1/0)	THU	0.14	0.35	4802
Friday	Dummy (1/0)	FRI	0.14	0.35	4802
Saturday	Dummy (1/0)	SAT	0.14	0.35	4802
Sunday	Dummy (1/0)	SUN	0.14	0.35	4802
Driving vehicle for commuting	Dummy (1/0)	CARDRV	0.68	0.47	4802
Taking public transport for commuting	Dummy (1/0)	PT	0.22	0.42	4802
Predicted probability working in office only commuting during peak hours	0 to 1	PKJI1	0.21	0.10	4802
Predicted probability working in office only commuting during off-peak hours	0 to 1	PKJI2	0.18	0.09	4802
Predicted probability hybrid work commuting during peak hours	0 to 1	PKJI3	0.05	0.02	4802
Predicted probability hybrid work commuting during off-peak hours	0 to 1	PKJI4	0.06	0.03	4802
Predicted probability working from home only	0 to 1	PKJI5	0.17	0.09	4802
Predicted probability not working	0 to 1	PKJI6	0.32	0.29	4802
Predicted conditional probability of the above six choice options	1 to 6	PK_JI	3.30	2.32	4802
Predicted probability working in office only	0 to 1	PKMO	0.39	0.19	4802
Predicted probability hybrid work	1 to 1	PKHYB	0.12	0.05	4802
Predicted probability working from home only	2 to 1	PKWFH	0.17	0.09	4802
Predicted probability not working	3 to 1	PKNW	0.32	0.29	4802
Selectivity correction (SC) for "working in office only"	number	SC1	-1.24	0.61	4802
Selectivity correction (SC) for "hybrid work"	number	SC2	-2.16	0.40	4802
Selectivity correction (SC) for "working from home only"	number	SC3	-1.93	0.59	4802
Selectivity correction (SC) for "not working"	number	SC4	-1.52	0.73	4802