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Time Allocation of Reduced Commuting Time during COVD-19 under Working from Home

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ABSTRACT:

The COVID-19 pandemic has had a significant impact on the amount of weekly commuting activity, with a commensurate increase in remote working, especially from home. The reduction in the amount of commuting time has resulted in time released for other activities. In this paper we identify the incidence of released time to paid work, unpaid work and leisure, and investigate the key drivers of this allocation. The findings are important in obtaining estimated time benefits from reduced commuting activity with such travel time being traded against work and against leisure, and what this might mean for the future travel, activity location, and lifestyle landscape.

KEY WORDS: ***COVID-19; working from home; Australian experience; time saved from commuting; reallocated time; leisure and work time.***

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1. Introduction

The adage that 'time is money' has been with us for a long time, with a large amount of evidence suggesting that individuals are willing to pay a positive sum to save a unit of travel time in the majority of travel activities (see Hensher (2011) for a review). When time in travel is saved, we have well-known theories that explain the value implications this has on whether this saved time is allocated to leisure or work (Jara-Díaz 2007). The trade-off between travel and leisure, and between travel and work, underpins much of the economic theory on the allocation and valuation of travel time, with varying constraints associated with these trade-offs (Jara-Díaz 2000, Jara-Diaz et al. 2008). A particular focus for the value of time has been that spent commuting, given that commuting activity is often a necessary (and typically viewed as a negative) by-product of work and thus unavoidable, and via the creation of accentuated peaks of travel demand in morning and afternoon peak periods, places large pressures on transport networks. As such, time spent commuting has been studied in a variety of ways.

1.1. Negatives of Time Spent Commuting

From a health perspective there have been a number of studies that have explored the impact of commuting, such as pain, dizziness, exhaustion and sleep deprivation (Haefner et al. 2001) and lower life satisfaction (Stutzer and Frey 2007). Morning commuting is particularly unpleasant (Kahneman and Krueger 2006) and commuting also impacts on satisfaction of time allocation to family life housework, childcare, and physical and leisure activities (Lorenz, 2018). On the other hand, working from home, walking to work and shorter commute times increase job satisfaction and shorter commute times make it more likely that an employee will stay with their job (Chatterjee et al. 2017).

1.2. Positives of Time Spent Commuting

While commuting is generally thought to be a negative downside to working, there is also research exploring the value that can be extracted from time spent during the commute, stemming from the value of travel more broadly. Mokhtarian and Salomon (2001) outline that travel is not exclusively a derived demand, rather it can be the constituent reason for the activity, and for the reason of enjoyment of travel (such as the sensation of speed, motion, and control, and the scenery through which a person travels), people may be motivated to undertake excess travel even in the context of mandatory or maintenance trips. In addition to these motivations, the act of commuting may also offer people the benefit of a defined transition between work and home, or indeed a break from home-based stresses (Edmonson, 1998), such that most people have a desire for some quantum of commute time even if the majority are commuting longer than they would like (Redmond and Mokhtarian 2001).

The daily commute is also less stressful for those who view the time spent commuting as productive (Ory and Mokhtarian 2005). Lyons and Urry (2005) present several hypotheses exploring how travel time can be productive time, and how that productivity might be enhanced in the 'information age'. A number of studies have explored the number and nature of activities that are completed while travelling (e.g., Zhang and Timmermans 2010, Tang et al. 2018) as well as how activity completion impacts both positively and negatively on satisfaction with the travel experience (e.g., Ettema et al. 2012, Rasouli and Timmermans 2014, Mokhtarian et al. 2015, Shaw et al. 2019).

1.3. The Use of Time while Commuting

A small number of studies have explored the impact that multitasking during the commute has on the value of travel time. In the Netherlands, Ettema and Verschuren (2010) find that those who do not engage in activities have higher values of time as do those who read for their work. Also in the Netherlands, Kouwenhoven and de Jong (2018) findings suggest that travellers who had a mobile phone, computing device, or music player available to them exhibited lower values of travel time over those who did not. Varghese and Jana (2018) find that the value of travel time savings in India was significantly reduced for individuals who engaged in multitasking. Nathan et al. (2019) also find that the value of travel time would be reduced if public transport users benefitted from mobile or internet connectivity, and Molin et al. (2020) find that relative to non-activity, the ability to conduct activities while traveling reduces the value of time, in particular for commuters who work or study while commuting. Recently in the US, Malokin et al. (2021) find that mode choices of millennials are strongly influenced by the activities performed while traveling, in particular exhibiting higher willingness to pay (in time or money) to use a laptop. Overall, Wardman and Lyons (2016) emphasise the need for more research on how the quality and productivity of "worthwhile use of time" impacts on appraisal approaches, given rising questions about whether or not the values of time used to assess transport investments are too high.

In terms of studies as to how commuters may apportion their time while travelling, de Jong and Kouwenhoven (2019) shows only minor increases in the time allocated to working for business trips (from 3% in 1988 to 6% in 2011, across all modes) even though the work was viewed as being just as productive relative to the normal environment. Perhaps in the closest pre-pandemic examination of how commuters may repurpose reductions in travel time, in developing a model of activity type choice, duration and productivity, Pawlak et al. (2017) show that many travellers would take any reductions in travel time as additional leisure time rather than dedicating additional time to work. Arguably, there is often the assumption in travel behaviour and appraisal studies that with relatively fixed working hours, the saved time is used in increased leisure activity as reflected in the value of commuting time linked back to a trade-off between leisure and travel.

1.4. The Commute and COVID-19

But what now for commuting? Since the start of COVID-19 pandemic, lockdowns and measures aimed at restricting the movement of people have resulted in a seismic shift in the way in which work is performed, not only in terms of location such as working from home, but also in terms of when that work is completed (Beck and Hensher 2020, 2020a). Furthermore, we currently observe a perception of this work time being undertaken remotely with at least the same level of productivity than prior to COVID-19 at the regular office location for many occupation classes. This is in part explained by the greater flexibility to be able to complete most work tasks remotely at a time that suits the employee, as opposed to the traditional 9am to 5pm weekday period. With working from home (WFH) likely to exist in the foreseeable future, to varying extents, this means that the amount of weekly commuting time will be reduced for a significant number of workers. While other studies have begun the investigation into what impact these changes may have on the value of commuting time used for transport appraisal (Hensher et al. 2021), much like how research has examined how people used their time while commuting, there is now also the question as to what the changes to remote working and flexible working hours mean for the extent of reduced commuting time, and how that 'saved' time is re-allocated to other activities?

In the US, Barrero et al. (2020) have found that about 35% of the time savings have been redirected to work related to primary employment, and about 60% to household chores and childcare. The allocation of time savings is broadly similar for men and women and across groups defined by race and ethnicity, but it differs substantially by education group and between persons with and without children at home. Our own ongoing surveys during the pandemic 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 such as going for leisurely and fitness walks (Beck and Hensher 2021)[1]. Overall, while the reallocation of time spent on different activities may be associated with saving in commuting time, it is also important to recognise that some may be associated with a broader rearrangement of the use of time, additional to reduced commuting time, simply by being at home for a greater period of time and needing to undertake other activities to compensate for changes in access to facilities and services such as gyms and clubs that are often closed or subject to stringent capacity constraints and social distancing.

If reduced commuting time enables a higher incidence of leisure time, this is in part related to the idea of social capital or relationship networks (Stanley et al. 2021) with activities that build social capital being ranked highly. Bridging and bonding social capital as an interpretation of available time, supports networking with other people, especially those in the household, developing potential through self-knowledge and personal growth, and adding to new experiences. Improving levels of bridging and bonding social capital both have monetary value.

1.5. Outline of the Paper

In this paper, we draw on data obtained from an online survey undertaken in March-August 2021 as part of an ongoing study of working from home and its implications for travel for residents in New South Wales (NSW) and Queensland (QLD). During this survey period neither jurisdiction was in lockdown, and while significantly higher than pre-COVID-19 levels, the extent of working from home had fallen from the extreme conditions observed during the first stages of pandemic related restrictions. The main focus is on what happens to any travel time reallocated away from commuting to other activity classes as a result of increased working from home. This is of great importance and is a test of the extent to which the theoretical trade-offs between travel and work and travel and leisure, and work and leisure occur under the new era of a greater incidence of working from home. This is a novel contribution in providing new empirical evidence on the way in which 'saved' commuting time over a period (i.e., a week) is allocated to three main activity classes, namely paid work, unpaid work and leisure and furthermore what are some of the statistically significant influences on this re-allocation. We present two models: one mixed logit model to gain an understanding of the influences on the probability of saved commuting time being used in work and leisure activities, and two regression models to investigate the relationship between the percentage of time and the absolute amount of time allocated to these three activity classes as a function of the amount of available saved commuting time and other influences. We discuss the longer-term policy implications of the rearrangement of work and leisure on a number of important structural changes in society that transport and land use agencies are starting to work through.

2. The Descriptive Setting

2.1. Survey Overview

Data was collected as part of ongoing research (beginning in March 2020) into the impact of COVID-19 on travel and activity in Australia. The surveys have been found to be largely representative (c.f. Beck and Hensher 2020, 2020a, 2021a, 2021b). The analysis herein was conducted on Wave 4, which was collected approximately one year into the pandemic in March 2021. At this point in time Australia had largely managed to supress the health impacts of the pandemic, recording low numbers of deaths and at the time of data collection, COVID-19 transmission was almost exclusively limited to returning international travels within the hotel

[1] During the pandemic, time allocation (and indeed the impact on work more broadly) may be distorted by the impact of school closures; however, for most of the pandemic in Australia schools have remained largely open (with the exception of those in Victoria).

quarantine system. Indeed, in almost all states life had begun to return to some degree of normality: in New South Wales the public health order that required employers to allow their employees to work from home was removed three months prior. Despite the return of many freedoms, people were still working from home to a greater extent than prior to COVID-19 (thus still exhibiting time savings from reduced commuting).

The Wave 4 survey asked respondents questions about their current work (occupation, days of employment, location for each day including home, hours worked), relevant travel to work data (time of commute, commuting mode, available alternatives, trip duration and cost for each available mode), trip making activity by mode and purpose, and several attitudinal questions. For detailed discussion of these questions see papers such as Beck and Hensher (2021a, 2021b). The most important questions for this paper are derived from the set focused on the impact of working from home. The survey was online programmed in the Qualtrics software and respondents were recruited by a major online consumer panel provider.

Of importance for this paper, we asked respondents the duration and cost of their pre-COVID-19 commute, along with how many days they worked from home in a normal week prior to COVID-19 and how many days they worked from home in the week preceding their survey response. These questions allow us to calculate time and money savings due to working from home (or not). Where relevant, we then asked respondents what they were doing with the money they were saving from not commuting (saving it, spending it, etc). For those respondents who were saving time by commuting less (due to working from home more), we also asked them how they were reallocating that saved time. Specifically, they were asked how much of that saved time (in percentage terms) they spent on: work for which they received additional pay (paid work); work for which they were not paid extra (unpaid) work; and on family/leisure/other activities. The motivation for this question was to being to explore the productivity implications of working from home in more detail.

The Wave 4 survey was for the whole of Australia, but there was a particular emphasis on the states of New South Wales (NSW) and Queensland (QLD) given other objectives of the project. The most urban environments in Australia are Sydney, Melbourne and Brisbane, however Melbourne had a markedly different experience of the pandemic in terms of the impact of COVID-19, and the other smaller state capital cities were virtually unimpacted. The initial sample size was 2000 respondents, including 888 from NSW and 871 from QLD. Within these two states 998 respondents were in employment, with 270 (27%) still working some amount from home greater than before COVID-19. In this paper we use this sample 270 respondents who during the data collection period, while no longer in lockdowns and having relatively "normal" freedoms of movement, were still working from home to a greater extent than prior to COVID-19 (thus still exhibiting time savings from reduced commuting).

2.2. Descriptive Analysis

The incidence of saved commuting time allocated to paid and unpaid work and leisure is shown in Table 1 for the sample, for all of NSW and QLD and the two major metropolitan area in NSW, namely the Greater Sydney Metropolitan Area (GSMA) and South East Queensland (SEQ). The sample size for Regional QLD and Regional NSW was too small to separate out. We also include the amount of money saved from reduced commuting activity. The distribution of saved travel time associated with the number of days WFH is summarised in Figure 1, and the way in which money saved from less commuting is reallocated is summarised in Figure 2. Of the average 60.5 minutes per week (standard deviation of 107 minutes – See Figure 4) saved from commuting, 47.5% (standard deviation of 36.1%) is allocated to leisure, 29.1% (standard deviation of 32.7%)

to paid work and 23.4% (standard deviation of 28.2%) to unpaid work. The distribution of the proportion of work and leisure time in the sample by the number of days WFH is shown in Figure 3. The data speaks to the general redistribution of time due to increased WFH and varies noticeably between the geographical locations. The great majority of money saved is not allocated to a specific plan.

Table 1: Descriptive Profile of the Incidence of Commuting Time Re-allocation throughout a week

	Total Sample	QLD	NSW	GSMA	SEQ
Sample share (%) (note: Cols for Regional NSW and Regional Qld are not included)		38.9	61.1	53.7	33.7
Commuting time saved (mins per week)	60.5 (107)	60.5 (99.7)	60.5 (112.2)	63.2 (116.8)	58.5 (101.1)
Commuting cost saved ($ per week)	8.2 (20.5)	11.3 (27.5)	6.29 (14.4)	6.9 (15.3)	11.5 (29.1)
Time spent doing additional work that I receive pay for (%)	29.1 (32.7)	24.5 (31.6)	31.99 (33.1)	32.1 (33.4)	23.9 (31.2)
Time spent doing additional work for which I receive no extra pay (%)	23.4 (28.2)	24.4 (31.2)	22.80 (26.2)	22.0 (25.4)	23.3 (30.6)
Time spent on leisure or family (%)	47.5 (36.1)	51.1 (38.9)	45.2 (34.0)	45.9 (33.9)	52.8 (38.3)
Reallocation of money saved with no plans (%)	75.4 (43.1)	73.9 (44.1)	76.5 (42.5)	78.5 (41.2)	71.8 (45.2)
Reallocation of money saved for something specific (%)	12.3 (32.9)	13.04 (33.80)	11.8 (32.3)	10.77 (31.1	15.4 (36.2)
Reallocation of money saved for different commuting choices (%)	0.89 (9.3)	2.2 (14.6)	0.0 (0.0)	0.0 (0.0)	2.6 (15.9)
Reallocation of money saved on something else (%)	11.4 (31.8)	10.9 (31.2)	11.8 (32.3)	10.8 (31.1)	10.3 (30.5)
Reallocation of money saved with no plans (%)	75.4 (43.1)	73.9 (44.1)	76.5 (42.5)	78.5 (41.2)	71.8 (45.2)
Days per week WFH only	2.6 (1.8)	2.4 (1.8)	2.8 (1.8)	2.8 (1.8)	2.4 (1.8)
Days per week WFH at some point	3.0 (1.7)	2.7 (1.6)	3.2 (1.7)	3.2 (1.6)	2.8 (1.6)
Days per week Work (from any location)	4.3 (1.6)	4.2 (1.5)	4.3 (1.6)	4.3 (1.6)	4.2 (1.5)
Proportion of days WFH only	0.6	0.6	07	0.7	0.6

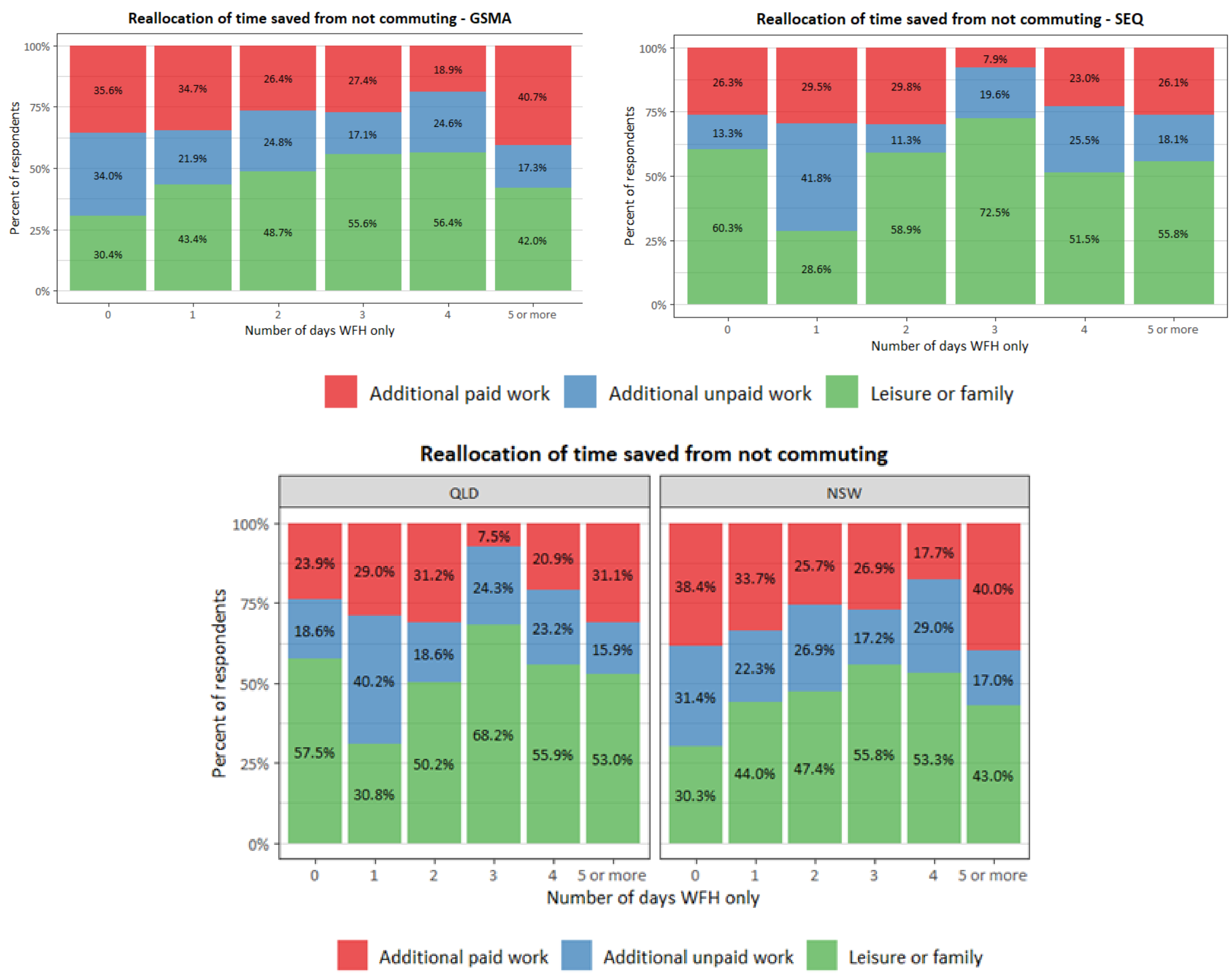

Figure 1. The incidence of work and leisure time as the number of days WFH varies

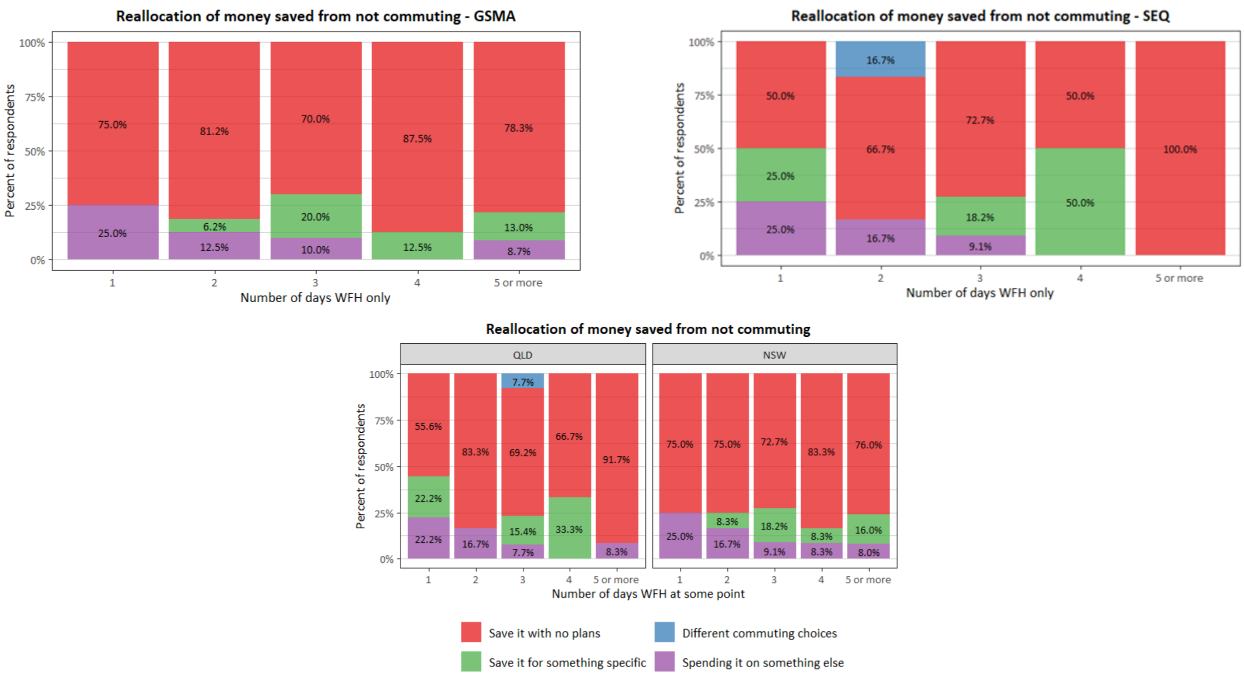

Figure 2. The allocation of money saved as the number of days WFH varies

Figure 3. The distribution of the proportion of paid work (PTIMPAY), unpaid work (PTIMFR) and leisure time (PTIMLEI) in the sample. Note: X axis is the proportion of time saved

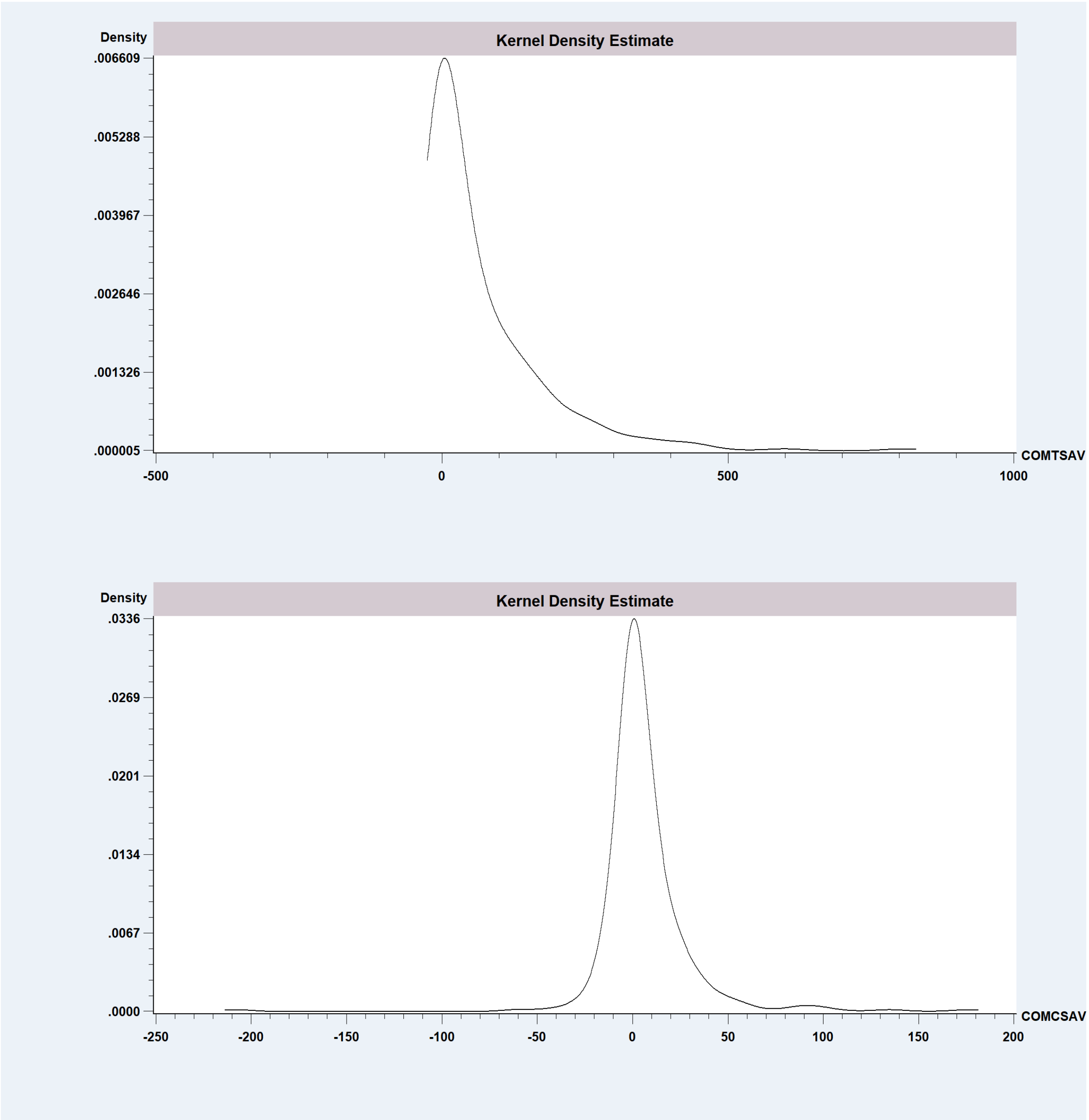

Figure 4. The sample distribution of commuting time saved (top figure) and money saved (bottom figure).

We use the findings above to obtain an estimate of the dollar value of the transferred time from commuting to leisure and work. To do this, we need to use an appropriate value of time (VoT) for each activity class. We use a value of time associated with leisure of $18.90/person-hour[2] and work as $45/person-hour obtained from other studies undertaken by Hensher et al. (2020). Using our data, we obtain a weighted average of annual time savings benefit (based on a 48-week commuting period) of $1,645 with a standard deviation of $2,921 (and range of $0 to $22,862). The average annual contribution of work and leisure respectively is $918 and $728, with respective standard deviations of $2,091 and $1,635.

In interpreting these findings, it is suggested in this age of smartphones that commuters do some amount of work while commuting both in public transport and in the car (Ory and Mohktarian

[2] Based on the modelling of commuting mode choice and WFH for the same data for both metropolitan and regional settings. See Hensher et al. (2021c).

2005), even if the activities are at the margin of a contribution compared to the average (Ref…). We know that the value of work time is higher than leisure time and so pre-COVID-19, we had assumed no change in the mix of leisure and work with little WFH, with most of time being traded between leisure and commuting with a fixed work time. During COVID-19, WFH and work overall increased, thus we can reasonably assume that the weighted average VoT will increase as the incidence of work when WFH (paid or unpaid) increases with travel-work being traded more than before compared to travel-leisure. In addition, Hensher et al. (2021b) showed that the VoT tends to increase as the number of days WFH increases, with an average 12.6% increase (in the GSMA) across the distribution of days WFH during COVID-19. We can obtain an estimate of what we refer to as the Price of Time (PoT) in contrast to the VoT by taking a simple ratio of the savings in money and time for each activity class and sum them, to obtain an average PoT of $23.55 per hour.[3] The PoT refers to the amount of time an individual has to forego in contrast to the VoT which is the amount of time an individual is willing to forego (Gronau 1974). This aligns well with the average VoT of $25.53 per person hour in the GSMA (Hensher et al. 2021b).

3. Time Allocation Models for Reduced Commuting Time

While the descriptive evidence is informative, we need to investigate sources of systematic variation in the allocation of the commuting time saved to each of the three activity classes. Two model forms have been used to seek out these sources of variation on time allocation; a mixed logit share model and single equations regression models for each activity allocation. The single equation models take two forms: the percentage of time allocated and the natural logarithm of the amount of time allocated. We are interested in seeing what socio-economic and other influences contribute to explaining differences in the share of saved time allocated to paid, unpaid and leisure time. An extended set of socioeconomic variables were collected and assessed together with a number of spatial variables shown in Appendix A. The rationale for the structure of the models is based on an initial consideration of a discrete-continuous choice framework, with the following sequence of investigations undertaken:

1. For the three continuous choice equations, we undertook a three stage least squares (3SLS) analysis which accounts for any possible endogeneity effects between the three allocations (putting an endogenous variable on both a LHS and a RHS within the system of equations subject to identification. These models did not obtain meaningful and statistically significant results and so we considered a SURE/2SLS approach where the correlated structures reside only in the random errors (so no RHS endogenous variables). Again, these models did not deliver statistically significant correlated errors and so we moved to separate equations.

2. In terms of connecting the discrete and continuous choice models, this is achieved by obtaining a probability of allocating time to a specific class and then adding this in as an explanatory variable in the continuous choice equations for each activity class along the lines of the well-known selectivity correction (see Barnard and Hensher 1992). This can be undertaken either simultaneously or sequentially, with the latter requiring corrections of the standard errors estimates using a method proposed by Murphy and Topel (1985). We initially used the sequential method, but the parameter estimates associated with this selectivity correction (based on the probability at an individual level of allocating time to a specific activity class) were not statistically significant. We also used the joint method in Barnard and Hensher (1992) which explicitly identifies the presence of a statistically

[3] We have added this informative evidence since in the mixed logit model in Table 2, the saving in money was not statistically significant and hence we were unable to obtain an inferred VoT. It makes sense that the money savings is not likely to be a significant influence on the allocation of saved commuting time

significant correlation between the discrete and continuous choices, in contrast to the MDCEV method developed by Chandra Bhat[4] (see for example La Mondia et al. 2008) where the latter does not explicitly obtain this correlated measure. We ultimately decided to focus on the approach reported in the paper; however, we provide an MDCEV model with elasticities in Appendix B.

3.1. Time Re-Allocation Mixed Logit

The mixed logit model results are summarised in Table 2[5]. We used an aggregate form of logit in which we can accommodate share data. In Nlogit6 we can handle share data in the 0% to 100% range and there is no need to discretise it. The left-hand side variable consists of a set of sample proportions. Values range from zero to one, and they sum to 1.0 over the set of choices in the choice set. Observed proportions may equal 1.0 or 0.0 for some individuals. Two variables are specified with random parameters to account for preference heterogeneity, namely the amount of commuting time saved in the paid work alternative and a person's age in the leisure alternative. The remaining five variables were not found to exhibit statistically significant standard deviation parameters and hence are estimated as fixed parameters. Although the overall goodness of fit is relatively low with a Pseudo-R^2 of 0.107, the statistical significance of the reported variables provides rich evidence on sources of systematic variation in the shares of time saved that is allocated to each of the three activity classes. The probability of a higher allocation to leisure increases with a person's age, and the number of cars in the household (which is correlated to some extent with household size and income) but decreases in the presence of a moderate to extreme concern over using public transport. In contrast to leisure, the probability of allocating a higher proportion of the saved time to paid work decreases as the absolute amount of saved time available increases, but this is cushioned by males tending to spend a higher proportion of time in paid work than females.

Occupation might be expected to have a role to play in the allocation of the saved time, and it is statistically influential for professional and administrators in the unpaid work alternative, with the negative parameter estimate suggesting that individuals in these occupation categories have a lower probability of allocating a higher proportion of the saved time to unpaid work. We considered the number of one-way weekly trips for each trip purpose and overall as well as the amount of money saved and none of these variables were statistically significant. We investigated region-specific dummy variable effects for all four locations and did not find any statistically significant influences associated with any of the alternatives in order to account for systematic differences on average in unobserved effects between the three activity classes. These findings seem plausible without a framework of empirical evidence to compare it against.

[4] Correspondence with the author revealed that there are no separate errors in the DC and CC parts in the traditional MDCEV model. In the working paper https://www.caee.utexas.edu/prof/bhat/ABSTRACTS/New_MDCEV.pdf correlation is engendered between the error terms of the DC and CC, but all correlations in the overall resulting multivariate logistic distribution are constrained to 0.5 to get a closed form solution. We believe this to be a restrictive assumption

[5] Using a multinomial logit form, we investigated interactions between socioeconomic and other variables such as commuting time as well as other variables and arrived at the model form we subsequently estimated as mixed logit where preference heterogeneity for age and commuting time were the only variables with statistically significant standard deviation parameters.

Table 2. The Mixed Logit Model of the share of commuting time saved that is allocated to a class of activity

Variable	Alternative	Estimated parameter (t-value)
Constant Leisure/Family	Leisure/Family	-0.4401 (-0.96)
Constant Paid Work	Paid Work	-0.3545 (-1.27)
Constant Unpaid Work	Unpaid Work	-
Age (years) - *mean*	Leisure/Family	0.0120 (3.20)
- *standard deviation*	Leisure/Family	0.0036 (3.20)
Number of cars in the household	Leisure/Family	0.2145 (2.54)
Concern about using PT (moderate and extreme) (1,0)	Leisure/Family	-0.6183 (-2.42)
Commuting time saving (minutes) - mean	Paid Work	-0.00476 (2.81)
- standard deviation	Paid Work	0.00048 (2.84)
Male (1,0)	Paid Work	0.8292 (2.98)
Professional occupation (1,0)	Unpaid Work	-0.3910 (-2.23)
Administration occupation (1,0)	Unpaid Work	-1.5129 (-3.06)
Restricted log-likelihood	***-296.625***	
Log-likelihood at convergence	***-264.745***	
Pseudo-R^2	***0.107***	
AIC/N	***2.028***	

The numerical extent of responsiveness is not identified from the parameter estimates but from elasticities given in Table 3 which summarises some key direct (in bold) and cross elasticities of the relationship between a unit change in an explanatory variable and the probability of allocating saved commuting time to a specific activity class. All are statistically significant. We see relatively inelastic estimates for all direct and cross effects, with the higher estimates for direct elasticities associated with age (0.25) and number of cars (0.27) in the leisure alternative, reaffirming the comments above that those individuals who are older and live in households with more cars tend to have a higher probability of allocating more time to leisure. Given that the amount of commuting time saved is only statistically significant for the paid work alternative, the mean direct elasticities suggest that, *ceteris paribus*, a 10% increase in available time saved from reduced commuting results in the probability of the paid work share reducing by 1%. At the mean, this is equivalent to 1% of the additional 6 minutes which is negligible given that 29.1% of time is allocated to paid work on average.

Table 3. Elasticity results (estimate in bold is the direct elasticity) (t-values in brackets)

		Probability of allocating time to…		
Attribute	**Alternative**	**Paid work**	**Unpaid work**	**Leisure/Family**
Age (years)	Leisure	-0.21 (-44.3)	-0.22 (-45.2)	**0.25 (41.3)**
Number of cars in household	Leisure	-0.24 (-30.3)	-0.25 (-30.1)	**0.27 (44.5)**
Concern (moderate and extreme) about using public transport (1,0)	Leisure	0.09 (13.9)	0.10 (13.8)	**-0.16 (-14.3)**
Total time saved (mins)	Paid Work	**-0.10 (-12.1)**	0.03 (11.5)	0.03 (7.8)
Admin occupation (1,0)	Unpaid work	0.03 (7.98)	**-0.27 (-8.2)**	0.03 (7.9)

We undertook a simulation of the relationship between the probability of allocating saved commuting time to each activity class as age and commuting time varies (Figure 5). We find that as the amount of time saved from reduced commuting increases, *ceteris paribus*, the probability of allocating a higher quantum of time to leisure and unpaid work increases and decreases for paid work. The rate of change is similar for leisure and unpaid work as the amount of commuting time saved increases, although the latter has a lower probability, suggesting that the main substitution is between paid work and both unpaid work and leisure. The simulation results in our sample suggest that, *ceteris paribus*, if a respondent saves less than 100 minutes as a result of less commuting, then they will allocate more of this time doing paid work than unpaid; but this will be opposite for a respondent saving more than 100 minutes as a result of less commuting. In the case of an individual's age, as age increases, *ceteris paribus*, the probability of allocating a higher quantum of time to leisure increases significantly, while it decreases for both paid and unpaid work at a similar rate, suggesting approximately equal substitution between all work and leisure activities. The results show that, *ceteris paribus*, a respondent who is 50 years old tends to allocate half of their saved time from not-commuting to leisure, around 30% to paid work and 20% to unpaid work.

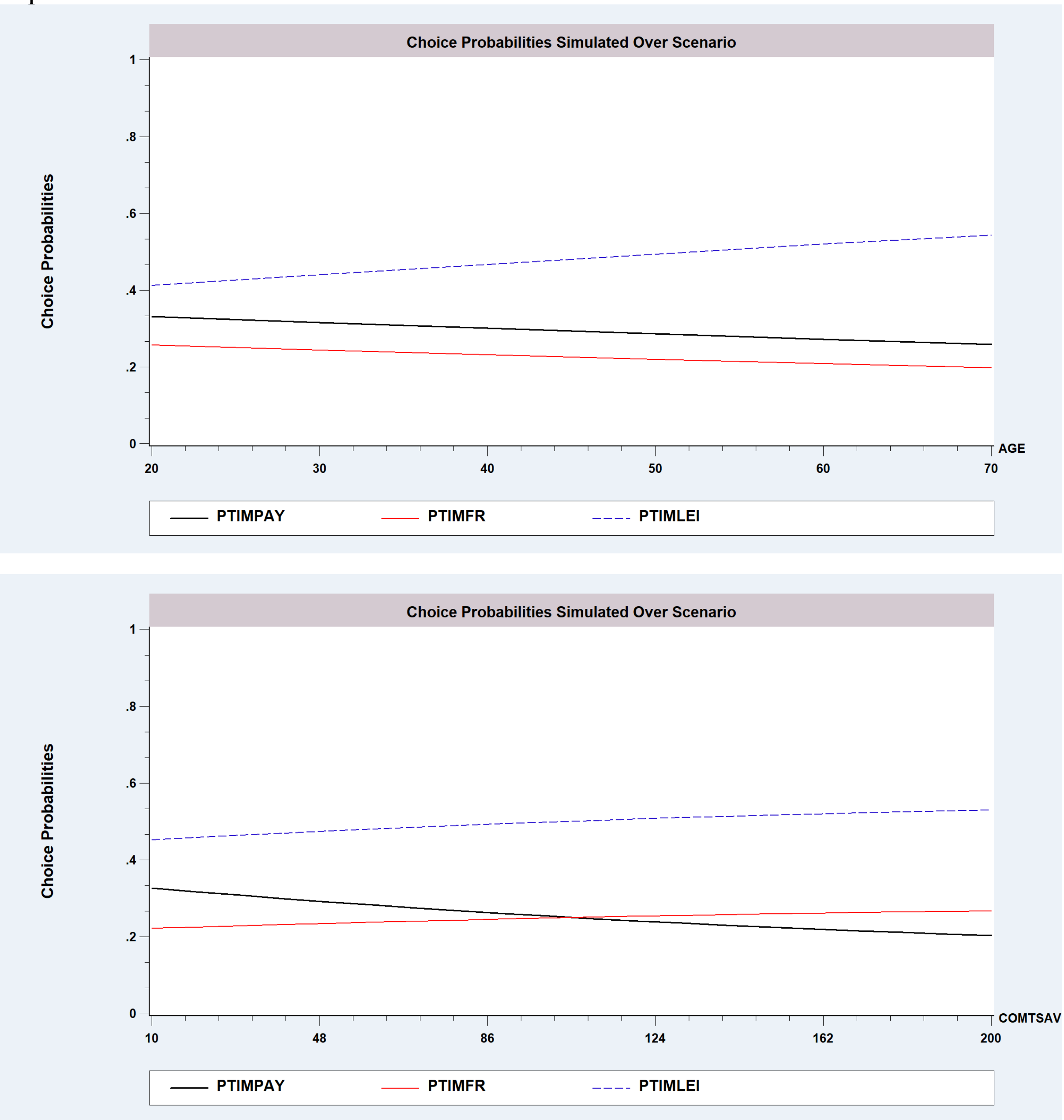

Figure 5. Simulation of the relationship between the probability of allocating saved commuting time to paid work (PTIMPAY), unpaid work (PTIMFR) and leisure time (PTIMLEI)as age (top graph) and commuting time (Comtsav) (bottom graph) varies.

3.2. Time Re-Allocation Regression Models

Two specifications of the standalone regression models were investigated. The re-allocation of the absolute amount of time and its share across the activity classes both have behaviourally interesting implications. The model focussing on the absolute amount of time allocated to each activity class enables us to identify sources of systematic variation in the amount of time re-allocated to an activity class, in contrast to a model where the interest is in the proportion of such time allocated to each activity class.

The results for the standalone regressions models for each alternative of time allocation are given in Tables 4 and 5 for two different specifications of the dependent variable: natural logarithm[6] and percentage. The models where the dependent variable is the natural logarithm of travel time allocated to an activity class, have a significantly improved overall goodness of fit (in the range of 0.93 to 0.788 across the three models) compared to the model where the emphasis is on the percentage of time allocated to each activity class (from 0.083 to 0.142). Both are informative, but we begin with the better fitting (in a statistical sense) model set.

The most interesting results relate to the amount of time saved overall from reduced commuting and its allocation. The parameter estimate for this variable in Table 4 is a direct elasticity estimate since both the dependent and explanatory variables are logarithmic. As an example, a 10 percent increase in the total amount of time saved results in a 7.574 percent increase in the amount of time allocated to leisure, holding all other influences constant (including the allocation to work). The percent increase in paid and unpaid work if there was a 10 percent increase in saved commuting time, ceteris paribus, is considerably lower, respectively an increase of 5.06 percent for unpaid work and a decrease of 3.08 for paid work. What we are seeing is that as the quantum of commuting time saved increases, there is evidence of the additional time being disproportionately allocated to leisure, unpaid work and paid work, with leisure being the winner. This is an important finding supporting theories of social capital (Stanley et al. 2021).

Another relevant finding is the relationship between the allocation of saved time to specific activity classes and the amount of one-way weekly travel for various trip purposes[7]. As the number of one-way weekly education trips increases, *ceteris paribus*, we observe a logarithmic increase in the amount of the saved time allocated to unpaid and leisure activities. An increase in the work-related one-way trips is associated with a logarithmic reduction in the amount of time allocated to unpaid work. There is no statistically significant relationship between any specific trip purpose weekly travel and the amount of time on paid work, but an increase in the total number of one-way weekly trips is associated with a logarithmic increase in the amount of time allocated to paid work. This is an important finding that suggests that reduced commuting activity with increased working from home does influence the amount of one-way weekly trips by various trip purposes as a result of released travel time that is redirected, to some extent, to non-commuting travel. For the explanatory variables that are not logarithmic (i.e., all except for the total time saved), we can interpret the relationship as follows: for every 1% increase in an explanatory variable, the dependent variable increases by 0.001 (i.e., the elasticity value as a percent). Hence, for every 10% increase in the number of one-way weekly education trips (e.g., from the mean of 1.95 to 2.15), the amount of time saved that is allocated to leisure activities increases by 0.389%. These are small but statistically significant changes.

The other influences on the amount of time allocated to an activity class are gender and three occupation categories, namely professional, administration and sales. Males tend to use the

[6] We estimated a model with absolute minutes but it was not as good as the logarithmic transformation. Indeed, we tested a very large number of models to arrive at the ones reported in the paper which are behaviourally sensible and having the best statistical fit.

[7] The trip purpose one-way weekly trips variables were not statistically significant in the mixed logit model.

reallocated time to undertake more paid work than females, while professional and administrative employees (and employers) tend to have higher amounts of this saved time allocated to leisure than other occupation classes; however, the opposite is the case for unpaid work (with except of sales which is not statistically significant for unpaid work).

Table 4. Standalone models for quantum of time re-allocation
Dependent variable is the natural logarithm of amount of time allocated. T-values are in brackets for the parameter estimates, and standard deviations for the levels of the variables.

	Average (std deviation)	Ln of Time Paid	Ln of Time Unpaid	Ln of Time Leisure/Family
Dependent variable - mean (std deviation)		***0.635 (1.39)***	***0.974 (1.65)***	***1.270 (2.04)***
Constant		-0.308 (-3.44)	0.3498 (4.23)	-0.2992 (-3.73)
Ln (total saved time)	1.969 (2.35)	0.3102 (7.96)	0.5060 (13.5)	0.7574 (24.1)
Total one-way weekly trips (all purposes)	19.76 (28.0)	0.0032 (1.56)		
Male (1,0)	0.485	0.5494 (3.77)		
One-way weekly work-related trips	1.87 (4.18)		-0.0503 (-2.31)	
One-way weekly education-related trips	1.95 (4.91)		0.0353 (2.00)	0.03889 (2.51)
One-way weekly visit elderly trips	1.04 (3.39)			-0.0732 (-2.12)
Professional occupation (1,0)	0.33		-0.5503 (-3.39)	0.4256 (2.78)
Admin occupation (1,0)	0.20		-0.8192 (-4.70)	0.5681 (4.48)
Sales occupation (1,0)	0.059			0.3706 (3.40)
Adjusted R-squared		***0.293***	***0.540***	***0.788***

In Table 5, we were able to identify a nonlinear relationship between the percentage of saved time allocated to leisure and to paid work and the total available time saved from reduced commuting (shown as Figure 6 and Table 6). As the amount of weekly commuter time saved increases, *ceteris paribus*, the percentage of weekly time outlaid on leisure activities increases at a decreasing rate up to 550 minutes and then progressively decreases at an increasing rate beyond 550 minutes of weekly commuting time saved. For paid work, the percentage of weekly time outlaid decreases at a decreasing rate up to 450 minutes, and then progressively increases at an increasing rate beyond 450 minutes.

The number of one-way weekly trips by various trip purposes are also statistically significant influences on the percentage of saved commuting time allocated to each of three activity classes. However, their influence is not the same in magnitude or direction in Table 4 for the absolute amount of time allocated. We see that there are four trip purpose weekly trip categories having an influence on the percentage of time associated with unpaid work: education and general shopping having negative parameters and work-related and food shopping having positive parameters. Thus, for example, if there is an increase in the number of work-related weekly trips from the average of 1.87 to 2.87 trips, this will result in a 1.633 increase in the absolute percentage of time allocated to paid work, from 29.1% to 30.7%.

These findings offer many possibilities for how we might gravitate to a new structurally informed future in which reduced commuting activity and the release of time for other activities will generate changes in a wide range of activities associated with travel and lifestyle. We address these in the concluding section below.

Table 5. Standalone models for percentage of time re-allocation

Dependent variable is the percentage of amount of time allocated. T-values are in brackets for the parameter estimates, and standard deviations for the levels of the variables.

	Average (std deviation)	Percentage of Time Paid work	Percentage of Time Unpaid Work	Percentage of Leisure/Family Time
Dependent variable – mean (std deviation)		*29.08 (32.8)*	*23.43 (28.27)*	*47.49 (36.14)*
Constant		27.39 (7.83)	29.51 (8.82)	39.76 (12.93)
Total time saved (mins)	60.47 (107)	-0.12003 (-4.15)	0.01586 (1.08)	0.0996 (2.72)
Total time saves squared/100	151 (529)	0.01294 (2.84)		-0.0094 (1.98)
Ln (total saved time)				
Total one-way weekly trips (all purposes)	19.76 (28.0)			
Male (1,0)	0.485	12.268 (3.21)		
One-way weekly commuting trips	4.8 (6.5)		0.6072 (2.86)	
One-way weekly work-related trips	1.87 (4.18)	1.6333 (2.63)	-1.324 (-2.53)	
One-way weekly education-related trips	1.95 (4.91)	-1.8259(-4.77)	0.8235 (1.97)	1.0697 (3.01)
One-way weekly food shopping trips	3.34 (5.07)	1.0699 (3.76))		-0.9341 (-2.80)
One-way weekly general shopping trips	2.08 (3.75)	-1.0298 (-1.97)		
One-way weekly social and recreational trip	2.99 (6.95)		-0.2729 (-2.34)	
One-way weekly visit elderly trips	1.04 (3.39)			
Professional occupation (1,0)	0.33		-9.580 (-2.25)	
Admin occupation (1,0)	0.20		-22.754 (-5.56)	20.828 (3.85)
Sales occupation (1,0)	0.059		-8.618 (-1.78)	
Adjusted R-squared		***0.15***	***0.090***	***0.085***

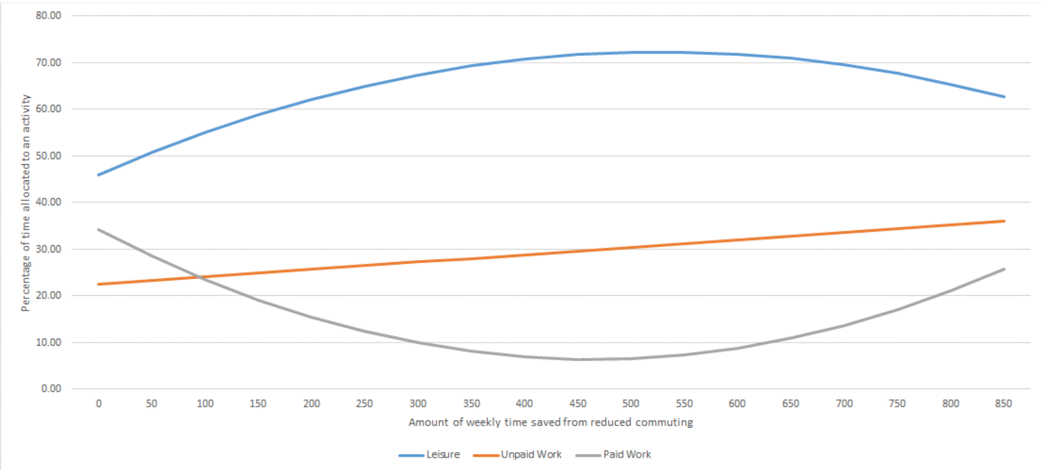

Figure 6. Non-linear relationship between the total amount of time saved from reduced commuting and the percentage of time re-allocated to each activity class

Table 6. Non-linear relationship between the total amount of time saved from reduced commuting and the percentage of time re-allocated to each activity class

Weekly time saved from reduced commuting (mins)	Leisure/Family time allocation (%)	Unpaid work time allocation (%)	Paid work time allocation (%)
0	46.01	22.52	34.27
50	50.76	23.31	28.59
100	55.03	24.10	23.56
150	58.84	24.90	19.17
200	62.17	25.69	15.44
250	65.03	26.48	12.35
300	67.43	27.28	9.90
350	69.35	28.07	8.11
400	70.80	28.86	6.96
450	71.77	29.65	6.46
500	72.28	30.45	6.60
550	72.32	31.24	7.39
600	71.88	32.03	8.83
650	70.98	32.83	10.92
700	69.60	33.62	13.65
750	67.75	34.41	17.03
800	65.44	35.21	21.06
850	62.65	36.00	25.73

4. Discussion and Potential Implications

The focus on how time saved though reduced commuting is converted into work and leisure time as well as how this results in changes in the amount of travel activity for specific trip purposes is important for understanding the longer-term potential implications of increased working from home (or remote work more general) and reduced commuting activity. The empirical findings in this paper relate to a specific period in the COVID-19 pandemic, 15 months after the initial outbreak, and in the case of Australia during a period of no lockdown and a high degree of measured activity. The evidence enables us to start speculating[8] on what the future may look like as we come to live with COVID-19 (under an almost fully vaccinated population) but with established support from employees and employers for maintaining some amount of remote working, at levels we suggest were observed in the period of the data used in this survey (given in Figure 7 at June 2021, defined as Wave 4).

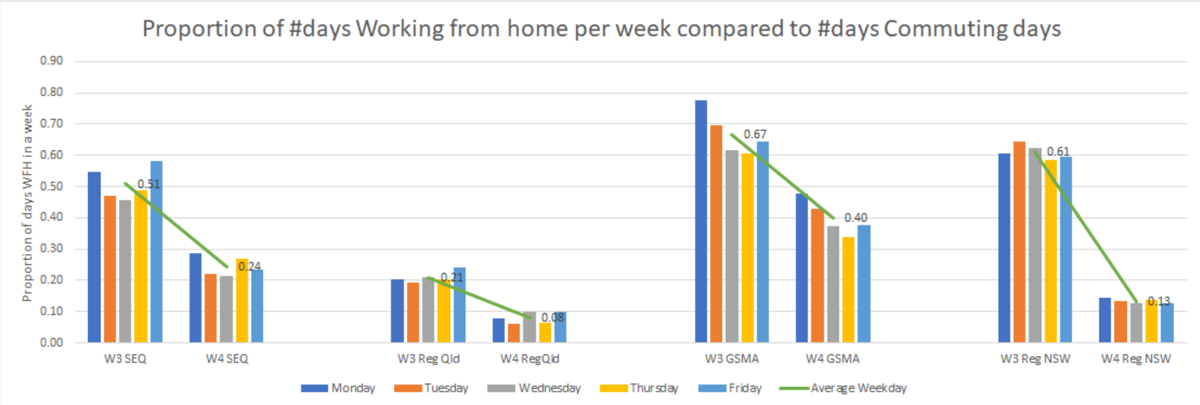

Figure 7 The observed proportion of days WFH in September 2020 and June 2021.

The increased quantum of time saved from commuting and converted into additional work and leisure should become part of the story of the future, being input into painting a picture of what the next 10 years may look like in terms of changes in travel and land use patterns of behaviour. We have attempted to translate this evidence into what we suggest it may signal (at least contribute to with other influences identified in other papers by Beck and Hensher 2002, 2021) for structural changes that are likely to occur as we learn to live with COVID. In the remaining paragraphs we set out what we speculate this future may well encompass as informed by our suite of research activities.

4.1. Changing Working Context

A defining outcome will be that more people will WFH to some extent, likely averaging 1 to 2 days a week in what has been broadly termed a hybrid model (with fluctuations around this in the next few years) and using the reduction in commuting time to engage in increased leisure and work activity. Flexibility and convenience and reluctance to go back to pre-pandemic working norms will be key drivers of this outcome with norms around WFH being redefined. While there are advantages and disadvantages to working from home, in a non-lockdown circumstance where children are at school and businesses are open, but biosecurity conditions are front and centre, the positives seemingly outweigh the negatives. Working from home during COVID-19 has likely had a larger impact on women in families with children (particularly during periods of lockdown where

[8] We openly acknowledge that this commentary is largely speculative, but we engage in this discussion as a way of promoting robust academic discourse. We note that one must always be careful when extrapolating short-term changes into the long-term.

schools have been closed) while prolonged working from home during lockdown periods may result in more women leaving the workforce. Conversely, it may also be possible that woman could return to the workforce if they could work from home. While a recurring finding is that women carry the bulk of the domestic responsibilities while working flexibly, government and business should view more flexible working arrangements through a less gendered lens, giving families more choice in how make work and care decisions, with the ultimate potential being for workforce participation of women.

Working from home has also become a key factor in the value proposition of different places of employment. Surveys conducted by the BBC (2021) in the United Kingdom show that 60% of workers want to work from home at least some of the time, along with a large increase in the number of job adverts referencing flexible working arrangements. A report by McKinsey finds similar results in the US, further noting a potential talent drain for companies that return to fully onsite work (Alexander et al. 2021). Many employees will want this option in their employment contracts - it will become part of negotiation. Organisational resilience will thus need redefining or recrafting and placed in the context of Figure 8, opening up continuing paid and unpaid work from home plus some additionally released leisure time with reduced commuting activity.

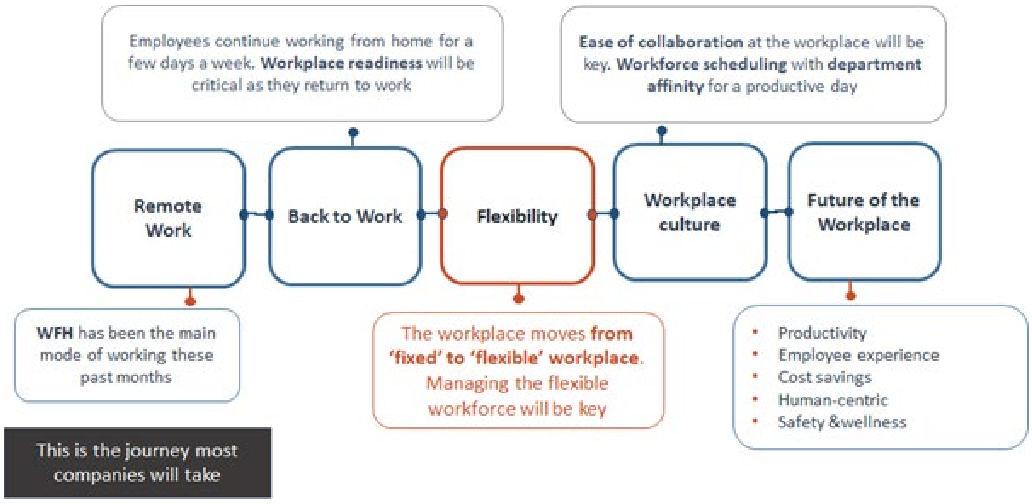

Figure 8 The move to remote working to some extent
Source: Revised diagram based on ideas from https://smartenspaces.com/solutions/hybrid-workplace

4.2. Travel and Location Impacts

With hybrid work settings, many high-density office hubs will have a reduced number of workers at any one time, typically 80% of pre-COVID levels (Beck and Hensher 2020b). We expect greater opportunities to provide satellite/third party office space under "office space as a service" (OSaaS), including new apartment blocks with a designated office floor ('commute to work by lift'). Density then becomes increasingly a bio-security risk linked to continuing nervousness in using public transport, especially if crowding returns, and indeed the associated higher density nodes in central metropolitan areas. Marginal residential relocation away from capital cities (exception maybe the second home) is likely to increase, noting that in Australia in the 12 months to the end of March 2021, 22,651 Melburnians moved to regional Victoria while 24,500 Sydneysiders moved to regional NSW; although a large amount was occurring regardless of COVID and WFH due to the regular cycle of residential mobility.

The enticement to relocate to outside of metropolitan areas will be driven strictly by better access and jobs in the regions. Residential choices are likely to be selected with more flexibility relative to work locations, and work locations will be chosen more flexibly relative to residential locations.

There is, however, a growing view that with a day or two working from home and three to four days in the office, big cities will not wither away[9]; however remote work is likely to move the city's borders to the edge of the metropolitan area, a reflection of expanding regional labour markets. Rather than drastically changing cities, WFH has subtly reimagined city life by giving more workers more flexibility. The Brookings analysis of the USPS migration data[10] concluded that remote work will settle into a new level, higher than pre-pandemic but lower than the present. The hybrid-work environment is pushing people to live within travelling distance near work, but not quite as close as they used to.

We can anticipate greater use of cars for all trip purposes and increased local (suburban) trip congestion (linked also with higher rates of passenger car registrations) in large measure due to the bio-security concerns in using public transport in particular: Google Mobility data has consistently shown car usage to rise to above pre-pandemic levels in many countries. Staggered working hours are hypothesised to contribute to changing levels of road traffic as a result of more single–occupant car use; spreading demand better over the day, with the level of traffic in the peak hours associated with commuting lowering as offices reduce capacity at any one time. However non-commuting traffic is also changing and some of this is moving to peak periods as a result of greater flexibility in when work is done, while also adding to traffic throughout the day, in both the traditional peak and off-peak periods. Finally, cost constraints on using the car to commute may also be reduced as a person travels to work fewer times during a given week. Additionally it has been shown that, for a variety of reasons, telecommunications and travel are complementary (Choo and Mokhtarian 2007), which could further lead to increased localised travel in particular by car.

How this change in car usage may impact on congestion is unknown at this stage and needs careful monitoring by transport authorities. Ideally, increased working from home would help reduce congestion and crowding due to a lower aggregate number of commuting trips. However, should barriers to car use be reduced (in particular cost) and to public transport be increased (due to bio-security concerns), we could see that when commuting is done the car because an even more dominant alternative. If this is the case, then transport authorities should work closely with business to ensure peak spreading is encouraged, and ultimately it may indeed strengthen the need for a more efficient form of road pricing than currently exists.
The quality of the living environment will become more important including larger units, an office at home, and enhanced digital connectivity. Linked to WFH, increased online activity by workers reinforces the possibility of a 15-30 minute city, a residential urban concept in which most daily necessities can be accomplished by either walking or cycling from residents' homes, which in the past has been especially hampered given it is mainly related to closer commuting locations with satellite offices.

4.3. Travel and Technology

All of these decentralised developments will impact technical and service innovations, such as autonomous cars, micro-mobility, (e)bikes and mobility as a service (MaaS). Electric cars, even with a distance based charge of 2.5c/km (promulgated in Victoria), are expected to encourage huge growth in small to medium sized electric cars, given that they will cost far less to purchase than the petrol-car as well as being less expensive to use[11], adding to congestion unless parking pricing

[9] https://www.businessinsider.com.au/remote-work-made-cities-bigger-nyc-san-francisco-metro-areas-2021-9
[10] https://www.brookings.edu/blog/the-avenue/2021/06/24/remote-work-wont-save-the-heartland/

[11] In Australia, the Electric Vehicle Council suggests that an EV's fuel cost will be 34.3 cents per kWh compared with average petrol cost of $1.36 per litre. This translates into 5.15 cents per kilometre for an EV compared to

comes to the rescue, in some locations. MaaS will have to build electric car sharing into its system to survive and especially where trips will increasingly be by car and not by air (for groups, especially families). Land-based long distance car travel looks like replacing a large amount of long distance international aviation in the immediate future at least, with improved and experienced digital communication killing off a significant amount of business related domestic aviation travel.

5. Conclusion

The COVID-19 pandemic has changed the nature of work for many, accelerating what has been a previously slow move towards flexible work and/or telecommuting. In this paper, building further on the result that one of most significant positive outcomes of working from home is not having to commute (e.g., Beck and Hensher 2020a), we have shown broadly how that time saved previously spent on commuting is reallocated; an approximate even split between additional paid or unpaid work (which has productivity dividends for business and the economy) and additional time spent on leisure or family activities (which has physical and mental health dividends for the individual, which will also likely impact positively on productivity). While it is likely that the change in work practices will persist, resulting in a permanent structural change in the nature of work for many, ongoing study of how workers are responding to less time spent commuting, and more time spent working from home, is clearly needed for some period of time yet, across multiple jurisdictions.

A particularly positive outcome of increased flexibility vis-à-vis the commute is that it has the potential to reduce congestion and crowding during peak periods raising new questions as to the value of these reductions to commuters who are still required or choose to travel to work? Perhaps most interestingly, how does increased levels of working from home change the very nature of the commute? In a world with hybrid work models, it might be possible that the benefits of the commute (when the commute is undertaken) become even more pronounced, particularly if it represents a period of defined separation between work and home, or part of a conduit to greater social interaction at a place of work. The nature and value of the commute will be particularly interesting to examine as COVID-19 continues to change the way we live, work and travel.

Finally, while the commute will continue to be a vexing issue into the future, albeit with a new and potentially more confounding set of considerations, the growing preferences and support to WFH and reduced quantum of commuting will not only influence the value of time associated with commuting (as shown in Hensher et al. 2021), but also the value attached to use of the time re-allocated from commuting. Both values must be included in transport appraisal as a way of obtaining the net benefit effect of WFH where the mix of time spent travelling, working and in leisure becomes the defining metric of the benefit of a revised composition of commuting and WFH time, where the latter is evolving as a legitimate alternative to travel. Changes in lifestyle and wellbeing as reflected in the use of time will become as relevant as the historical focus on crowding and congestion.

14.39 cents per kilometre for an internal combustion engine using petrol, an average saving of $1,275 per annum on fuel costs alone.

Appendix A: Socioeconomic and spatial variables

Table A1 Socioeconomic and spatial variables assessed for inclusion in the models

Variables	Mean (std deviation)
Age	41.02 (13.37)
Average personal annual income (AUD$000)	103.69 (64.50)
Number of people in the same house	3.16 (1.39)
Number of cars in your household	2.58 (0.90)
Number of children in household	0.73 (0.97)
Proportion who used car as driver to commute prior to COVID-19	0.73
Proportion of sample who are blue collar workers	0.10
Proportion of workers who have a high level of concern about using PT	0.44
Occupation professional (1,0)	0.33
Occupation manager (1,0)	0.25
Occupation sales (1,0)	0.06
Occupation clerical and administration (1,0)	0.20
Occupation community and personal services (1,0)	0.06
Occupation technology (1,0)	0.03
Occupation machine operators (1,0)	0.02
Occupation labourers (1,0)	0.04

Appendix B: MDCEV model

The MDCEV model represents a discrete-continuous choice-making process. The random utility function defined by Bhat (2008) has the following form:

$$U(x) = \sum_k \frac{\gamma_k}{\alpha_k} \cdot \left[\exp\left(\beta' z_k + \varepsilon_k\right) \right] \cdot \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\}$$

where γ and α are satiation parameters associated with each alternative k; x is the amount of time allocated to activity class k; z represent the attributes that represent activity class k; β its associated parameter estimates; and ε the error term. The random utility is maximised subject to a linear budget constraint, which is 100% in this study as it represents the percentage of the total commuting time saved. The error term is assumed to be independent of the z and assumed to be independently distributed across activity class with a scale parameter of σ, which can be normalised to 1 if there is no variation in unit prices across activity classes, which is the case in this study.

The closed form expression for the probability that the individual allocates time to the first M of the K activity classes is as follows[12]:

$$P(x_1^*, x_2^*, \ldots, x_M^*, 0, 0, \ldots, 0) = \frac{1}{p_1} \cdot \frac{1}{\sigma^{M-1}} \cdot \left[\prod_{i=1}^{M} f_i \right] \cdot \left[\sum_{i=1}^{M} \frac{p_i}{f_i} \right] \cdot \left[\frac{\prod_{i=1}^{M} \exp\left(\frac{V_i}{\sigma}\right)}{\left(\sum_{k=1}^{K} \exp\left(\frac{W_k}{\sigma}\right) \right)^M} \right] \cdot (M-1)!$$

where:

$W_k = \beta' z_k + (\alpha_k - 1) \cdot \log\left(\frac{x_k^*}{\gamma_k} + 1 \right)$, when the α -profile is used, which is what we did in this study.

$$f_i = \frac{1 - \alpha_i}{x_i^* + \gamma_i}$$

[12] This probability expression considers no outside goods, that is, the time allocation of any alternative can be equal to 0.

and p_i is the unit price of activity class i, which does not vary across alternatives in our study and assumed equal to 1. It is interesting to note that the probability expression depends on the order of activity classes, as it includes the cost of the first activity class, p_1; however, this does not influence our study as mentioned above. As explained in Bhat (2008), the MDCEV model is able to include flexible correlation patterns (e.g., error components) but it is not able to accommodate random taste variation. Therefore, the MDCEV model cannot replicate our MML model exactly, as the MML model considers random taste variation which appeared to be statistically significant in the model results.

The elasticities represent the percentual change in the probability of allocating time to an activity class k by 1% change in an explanatory variable. However, the MDCEV probability expression is not activity class-specific but represents a vector of time allocation. Therefore, if we vary one explanatory variable it will affect the probability of allocating time in all three activity classes and thus, the effect of the 1% change of the explanatory variable in the probability of allocating time in one activity class cannot be separated. The proposed form to calculate the elasticities is to assume that the probability to allocate time to one activity class is equivalent to the vector probability of allocating all saved time to that activity class. That is, in this study we have three activity classes to allocate time to: paid work, unpaid work and leisure, which can be written as $P(x_1^*, x_2^*, x_3^*) = P(x_{paid}^*, x_{unpaid}^*, x_{leisure}^*)$. Our proposal is to assume that the probability of allocating time to each activity class can be determined by the following allocation vectors:

$$P_{paid} = P(100,0,0)$$

$$P_{unpaid} = P(0,100,0)$$

$$P_{leisure} = P(0,0,100)$$

Using these assumptions, we calculated the elasticities between the probabilities of allocating time to each activity class and each explanatory variable.

The parameter estimates for the MDCEV with fixed parameters is presented in Table B1[13] and the elasticity results are presented in Table B2.

Table B1 MDCEV model results

Variable	Alternative	MDCEV fixed Mean	t-value
Constant Leisure	Leisure	-0.618	-1.364
Constant Paid Work	Paid Work	-0.846	-3.678
Constant Unpaid Work	Unpaid Work	-	-
Age (years) - mean	Leisure	0.017	2.458
- standard deviation	Leisure	-	-
Number of cars in the household	Leisure	0.191	1.799
Concern about using PT (moderate and extreme) (1,0)	Leisure	-0.683	-3.578
Commuting time saving (minutes) - mean	Paid Work	-0.005	-3.869
- standard deviation	Paid Work	-	-
Male (1,0)	Paid Work	0.787	3.756
Professional occupation (1,0)	Unpaid Work	-0.334	-1.515
Administration occupation (1,0)	Unpaid Work	-1.390	-4.580
MDCEV Alpha base parameter Alpha = 1 /(1 + exp(-alpha_base))	All alternatives	-10.509	-0.327
MDCEV Gamma parameters	Leisure	17.836	5.077
MDCEV Gamma parameters	Paid Work	33.717	4.999
MDCEV Gamma parameters	Unpaid Work	14.145	6.045
Log-likelihood at convergence			**-1649.871**

Table B2 Elasticity estimates using the MDCEV model (t-values in brackets)

		Probability of allocating time to…		
Attribute	**Alternative**	**Paid work**	**Unpaid work**	**Leisure**
Age (years)	Leisure	-0.1031 (28.1)	-0.1826 (32.1)	0.5979 (43.9)

[13] The MDCEV model was estimated using Apollo software (Hess & Palma, 2019).

Number of cars in household	Leisure	-0.0719 (28.5)	-0.1299 (30.8)	0.4216 (41.9)
Concern (moderate and extreme) about using public transport (1,0)	Leisure	0.9887 (30.1)	1.8152 (32.2)	-5.4168 (48.1)
Total time saved (mins)	Paid Work	-0.0784 (38.6)	0.0428 (21.9)	0.1372 (27.4)
Admin occupation (1,0)	Unpaid work	0.2945 (20.2)	-1.2167 (35.2)	1.6538 (31.1)

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