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Mobility as a Service and private car use: evidence from the Sydney MaaS trial

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ABSTRACT: Australia's first Mobility as a Service (MaaS) trial commenced in April 2019 in Sydney, running for two years. The objective of the trial is at least twofold – to assess interest in various MaaS subscription plans through bundling public transport, rideshare, car share and car rental with varying financial discounts and monthly subscription fees, in contrast to pay as you go (PAYG); and to assess the extent to which the use of the private car might change following a subscription to a monthly mobility bundle. This paper assesses the second objective by investigating the potential for changes in monthly car use in the presence of a MaaS program. The paper develops a joint discrete-continuous model system to explain the choice between monthly bundles and PAYG, and subsequently, the total monthly car kilometres. Controlling for monthly differences due to other influences such as seasonal travel activity, the findings suggest that the offered bundles do have an encouraging impact on private car use. Within the limits of what was tested under the Sydney MaaS trial, indicative evidence suggests that MaaS has the potential to change travel behaviour in a way aligned with sustainability objectives, although this evidence should not be taken as suggesting that MaaS is a commercially viable mobility strategy.

KEY WORDS: ***Mobility as a Service (MaaS), MaaS trial, Sydney, mobility bundles, Pay as you go (PAYG), MaaS subscription, Discrete-continuous model, Poisson regression, elasticities, marginal effects, car use***

AUTHORS: **Hensher, Ho and Reck**

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Introduction

Mobility as a Service (MaaS) has generated a huge amount of interest as a prospective way to garner a greater commitment to mobility activity that aligns with achieving sustainability objectives such as reducing road congestion and emissions. At the same time, MaaS gives travellers greater choices through targeted information on travel planning with the support of a digital platform (Sochor et al. 2016, Smith and Hensher 2020, Wong et al. 2020). In contrast to an almost-daily-commentary on the virtues of MaaS and a growing number of researchers questioning whether MaaS is scalable or niche, very few MaaS schemes present in real markets. There appears to be a plethora of digital platforms promoted as MaaS, even though most are trip planners with a pay as you go (PAYG) option. These enhanced digital platforms, typically in a smart-phone app, enable users to obtain information about travel options as well as booking of mobility services available on the platform. While this all sounds very appealing, we have yet to see a MaaS product that is a successful business model and which offers various multimodal bundles through a subscription plan, despite a number of applications such as Whim in Finland, Ubigo in Sweden, and swa Augsburg in Germany (see Hensher et al. 2020, Chapter 3 for details).

The Sydney MaaS trial, which commenced in April 2019 as a two year project, was designed to obtain contributing evidence on whether MaaS is a value added mobility proposition. It is the first MaaS trial in Australia, and has the following objectives: (1) To explore appropriate transport service mixes and subscription plans for early adopters of MaaS; (2) To generate first-hand knowledge of actual MaaS experiences; (3) To advance the understanding of user uptake and willingness to pay for MaaS; (4) To test the ability to influence travel behaviour through introducing MaaS solutions; and (5) To document the experience in designing, planning and undertaking a MaaS trial.

Partners in the trial are the Institute for Transport and Logistic Studies (ITLS) at the University of Sydney, The Insurance Australia Group (IAG) and Skedgo. The trial leveraged off of unique knowledge about potential MaaS users' preferences acquired through previous research at ITLS (Ho et al. 2018, 2020), as well as IAG's existing relationships with a wide range of transport service providers in Sydney and a strong customer/value design focus, and SkedGo's multimodal travel planner *TripGo*, which was modified for the trial as *Tripi*. A graphical representation of the main components of the trial are given in Figure 1.

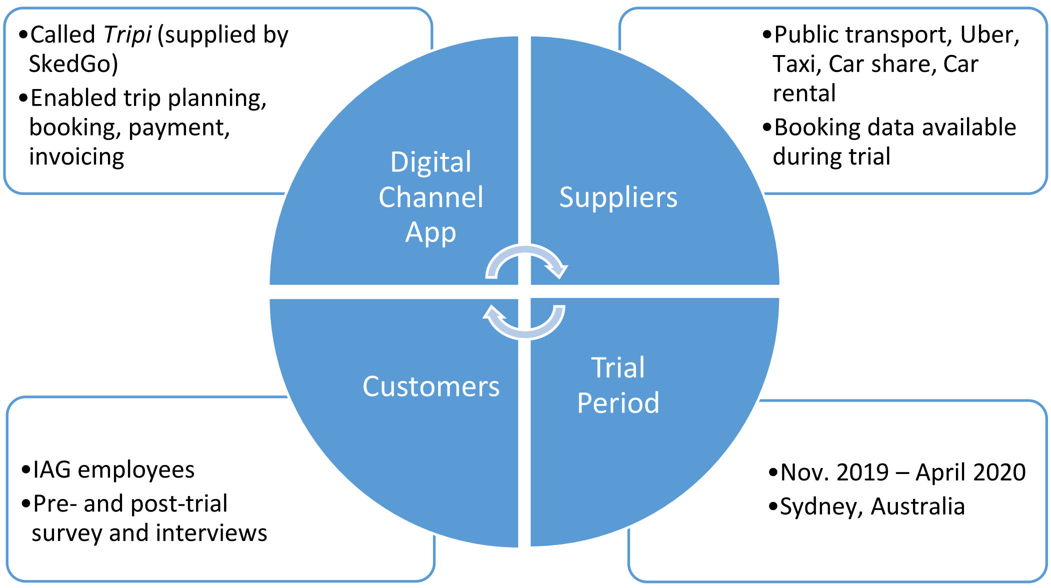

Figure1. The overall MaaS trial approach

This paper explores the relationship between subscription to a MaaS bundle in contrast to staying with PAYG and what influence, if any, the decision to subscribe to a bundle through choosing one of the offered bundles has on private car use. *Tripi*, the digital platform used in the trial, did not capture car use[1]; however, a complementary program called *Safer Journeys*, run by IAG, provided car use data for a subset of participants who also subscribed to this complementary program. Participants were asked whether they were involved in the Safer Journeys program and whether they would be interested in joining, and if they consent to sharing their Safer Journeys data with the MaaS Trial. The Safer Journeys trial was car-based with tracking technology installed so that car use kilometres can be measured, a crucial piece of data given the objective on reducing emissions through reduced car use.

The MaaS trial in Sydney adopted a data-driven incremental approach to the design of monthly bundles for the participants to subscribe to (See Figure 2). Yet, how do you design initial bundles before a trial has even started? Most importantly, and although the trial only officially started in November 2019, all participants were initially on-boarded as PAYG users. This allowed the participants to gain experience with the MaaS app while the trial team could collect initial booking data and combine it with data from the pre-trial survey to design a first bundle for December 2019. With each following month, more booking and tracking data was available to design the subsequent bundles and test both their economic viability and relative competitiveness against previous booking data. The latter was important as the trial team wanted to design a balanced set of bundles without dominant alternatives. Monthly bundles were thus gradually developed along the dimensions outlined in Reck et al. (2020) and introduced in December 2019 (‘Fifty50’), January 2020 (‘Saver25’), February 2020 (‘GreenPass’) and March 2020 (‘SuperSaver25’). Reck et al. (2020) review the growing number of papers that have investigated the role of bundles in MaaS. Two papers of particular interest are Caitai et al. (2020) and Feneri et al. (2020).

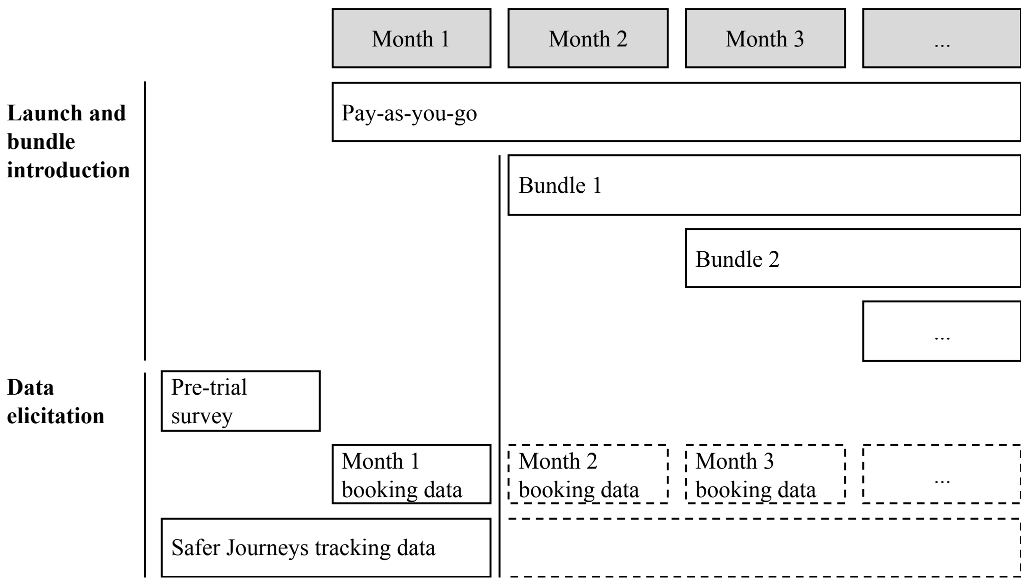

Figure 2. Sequential introduction of bundles

[1] Although the possibility of undertaking a journey by car was shown in the options, the use of the car was not tracked.

Figure 3 summarises these monthly bundles. Once introduced, the monthly bundles remained available for subsequent months of the trial, except for the Saver25 bundle[2] which was replaced in March by the SuperSaver25 bundle. The latter aims to encourage greater use of public transport through a financial incentive associated with the first and last mile (access and egress) part of a door-to-door public transport trip. Specifically, in addition to the Saver25 offers, the SuperSaver25 added a $5 Uber flat fare for the subscribers to connect to/from public transport trips. Free first and last mile trips were considered but were rejected due partly to the available incentive budget, and partly to a concern about the impact of this offer on existing bus services in accessing and egressing a rail station. The compromise was to introduce a financial incentive for Uber only (determined also by the way Uber is integrated into *Tripi*) with a distance cap option in order to provide absolute certainty to participants that they would not face different Uber fares for the same trip, for example, from their home to a local train station, regardless of the time of the day these trips were undertaken. Using distance (cf. fare) as a cap to define eligible Uber trips for the flat fare is important since Uber has a surge price (i.e., high demand price), which may result in a situation where users pay different fares for the same distance travelled. Analysis of data collected prior to the introduction of the SuperSaver25 bundle in March 2020 suggested that 75 percent of participants live within 5 kms of a train station, with PAYG users generally living slightly further from a train station than bundle subscribers.

In addition to this change to Saver25, renamed as SuperSaver25, we also changed the 15% on Taxi and Uber to be a flat $3 reduction, given feedback that participants preferred an absolute dollar amount. It became clear that most Uber and Taxi trips are relatively short, and so a $3 incentive is better value that a percentage, where the latter may be more appealing for long trips. We stayed with the subscription fee of $25/month and the 25 percent discount on all public transport trips. Car-based options were provided through GoGet and Car rental[3]. The take up of GoGet was essentially existing GoGet trips, and hence we did not see any benefit linked to the goals of the trial and removed the incentive. In the current paper, we take the bundles as given, with details on how they were designed in a forthcoming paper.

[2] This bundle has the same subscription fee and public transport discount as SuperSaver25 but rideshare had a 15% discount per ride instead of the $3 discount and there was no Uber discount for the first and last mile.
[3] In a Webinar hosted by Global MaaS Transit on April 17, 2020, by Sampo Hietanen, Founder & CEO, MaaS Global titled 'Mobility-as-a-Service - The End of Car Ownership?', in response to a question, Sampo said that ''the profitable part [of MaaS] is having access to a car on weekend otherwise MaaS is just a utility service.' The Sydney trial accommodated this feature through GoGet and car rental. This is also a position supported by research in Belgium by Storme et al. (2020).

Figure 3. PAYG and monthly bundles offers over the 5-month trial, current as of March 2020

The Joint Model System of Bundle Choice and Car Use

Formally, we have two models, one representing the choice between taking up a MaaS bundle and choosing to stay with PAYG, and the other the monthly kilometres travelled by a private car. This is a discrete-continuous choice model (simultaneous equation) system, where the discrete component is either a logit or probit form, and the continuous component is a count model such as a zero inflation Poisson regression. The binary choice model for PAYG versus a bundle is defined by a binary outcome y_i taking the values 0 (for PAYG) and 1 (for bundle) with the probability of choosing a bundle defined as:

$$\text{Prob}[y_i=1] = F(\beta' x_i) \text{ such that } F'(\beta' x_i) \geq 0 \text{ and } 0 < F(\beta' x_i) < 1. \quad (1)$$

We first estimate the binary choice model as logit by maximum likelihood to obtain estimated parameters for influences on a bundle vs PAYG choices, and then use the estimated model to compute, for each participant, a predicted probability of choosing a bundle. This probability is then fed into a Poisson regression model for monthly car kilometres (see below). The estimation at both steps is consistent; however we still need to correct the estimated asymptotic covariance matrix for the estimator at step 2 for the randomness of the estimator carried forward from the binary choice model. The standard Murphy and Topel (1985) correction is implemented, so that the standard errors and hence the t-values of the Poisson model are asymptotically efficient.

The amount of monthly car kilometres travelled by each participant in the trial is obtained from their participation in the Safer Journey's program. Monthly kilometres is a positive number compliant with a count model such as zero inflation Poisson (ZIP) with latent heterogeneity[4]. It is connected to the binary choice model by the method described above. As a non-negative continuous count value, with truncation at zero, discrete random variable, *Y,* observed over a period of length T_n (i.e., a month) and observed kilometres, y_n, (n observations), the Poisson regression model is given as equation (2).

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

$$\text{Prob}(Y = y_n|\mathbf{x}_n) = \frac{\exp(-\lambda_n)\lambda_n^{y_n}}{y_n!}, y_n = 0,1,...; \log\lambda_n = \boldsymbol{\beta}'\mathbf{x}_n. \quad (2)$$

In this model, λ_n is both the mean and variance of y_n; $E[y_n|\mathbf{x}_n] = \lambda_n$. We allow for unobserved heterogeneity as well as consider the ZIP form for count data (see Greene 2000) to recognise the possibility of partial observability if data on monthly kilometres being observed for any period within the four months exhibits no car uses[5]. Specifically, the answer 'zero' could arise from two underlying responses. If we were unable to capture any car use, we would only observe a zero; however, the zero may be due to the measurement period (i.e., a particular month) and the response might be some positive number in other periods. We define $z = 0$ if the response would always be 0, 1 if a Poisson model applies; y = the response from the Poisson model; then zy = the observed response. The probabilities of the various outcomes in the ZIP model are:

$$\text{Prob}[y = 0] = \text{Prob}[z = 0] + \text{Prob}[z = 1]\times\text{Prob}[y = 0 \mid \text{Poisson}] \quad (3a)$$
$$\text{Prob}[y = r > 0] = \text{Prob}[z = 1] \times \text{Prob}[y = r \mid \text{Poisson}]. \quad (3b)$$

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

$$\text{Prob}[Y_n = 0] = q_n + [1 - q_n]R_n(0), \text{ and}$$
$$\text{Prob}[Y_n = r > 0] = [1 - q_n]R_n(r) \quad (4)$$

where $R_n(y)$ = the Poisson probability = $e^{-\lambda_n} \lambda_n^{y_n} / y_n!$ and $\lambda_n = e^{\beta' x_n}$. We assume that the ancillary, state probability, q_n, is distributed normal; $q_n \sim$ Normal $[v_n]$. Let $F[v_n]$ denote the normal CDF. Then,

$$v_n = \tau\log[\lambda_n] = \tau\boldsymbol{\beta}'\mathbf{x}_n \quad (5)$$

Equation (5) defines a single new parameter (which may be positive or negative). If there is no (or little) evidence of zero kilometres in any observations, then we do not expect the τ parameter to be statistically significant, and we can default to the Poisson form with normal latent heterogeneity.

The two models are estimated using the combined data from the Safer Journeys program (monthly car use) and the data obtained from the *Tripi* app and the pre-trial survey. The former provided details of the bundles chosen each month and the latter socio-demographic information of each participants.

Descriptive Profile

Of the 92 participants of the Sydney MaaS trial, 33 participants were also the Safer Journeys Program subscribers. Car use of this subset of the MaaS participants, together with the MaaS monthly bundle subscription dataset, form the core datasets for this paper. It is worth mentioning that car use data prior to the MaaS trial was also available since the safer journey scheme was launched before the MaaS trial was conducted. However, for the purpose of assessing the impact of MaaS bundle subscription on private vehicle kilometres travelled, only safer journey data between the time when a participant joined the trial and when s/he left were extracted and used for analysis. This is because not every participant joined the MaaS trial in November 2019, and not everyone continued active up to the end of the trial in March 2020. Also, few participants were active in the MaaS program (i.e., made trips using the *Tripi* app) but did not undertake any car trips in specific months. These are included to avoid biasing the data. In total, the dataset represents 171 participant months. A summary of monthly MaaS bundle

[5] Fitting a simple Poisson model would overstate ('inflate') the theoretical probability of zero in the Poisson model. The ZIP model involves joint estimation of a count data model and a binary probit (or logit) model where the latter tests for whether the response will always be zero or otherwise (up to a probability).

subscriptions and the switching between PAYG and bundles for these 33 participants is summarised in Figures 3 (as absolute numbers) and 4 (as percentage of participants). Over the four months between December 2019 and March 2020 when monthly bundles were available for subscription, 52 bundle offers were accepted. This includes a participant staying with or switching away from a bundle, including moving between bundles but excluding moving from a monthly bundle to a PAYG option. Overall, for the 171 participant months, the Fifty50 bundle offered in December through to March was chosen 36.5% of the time; Saver25, introduced in January, was selected by 15.4% of participant months; and in February when we introduced the GreenPass bundle, its popularity in February and March resulted in the highest participant month uptake of 38.4% of all bundles. The SuperSaver25 bundle that replaced the Saver25 bundle in March represented 9.3%.

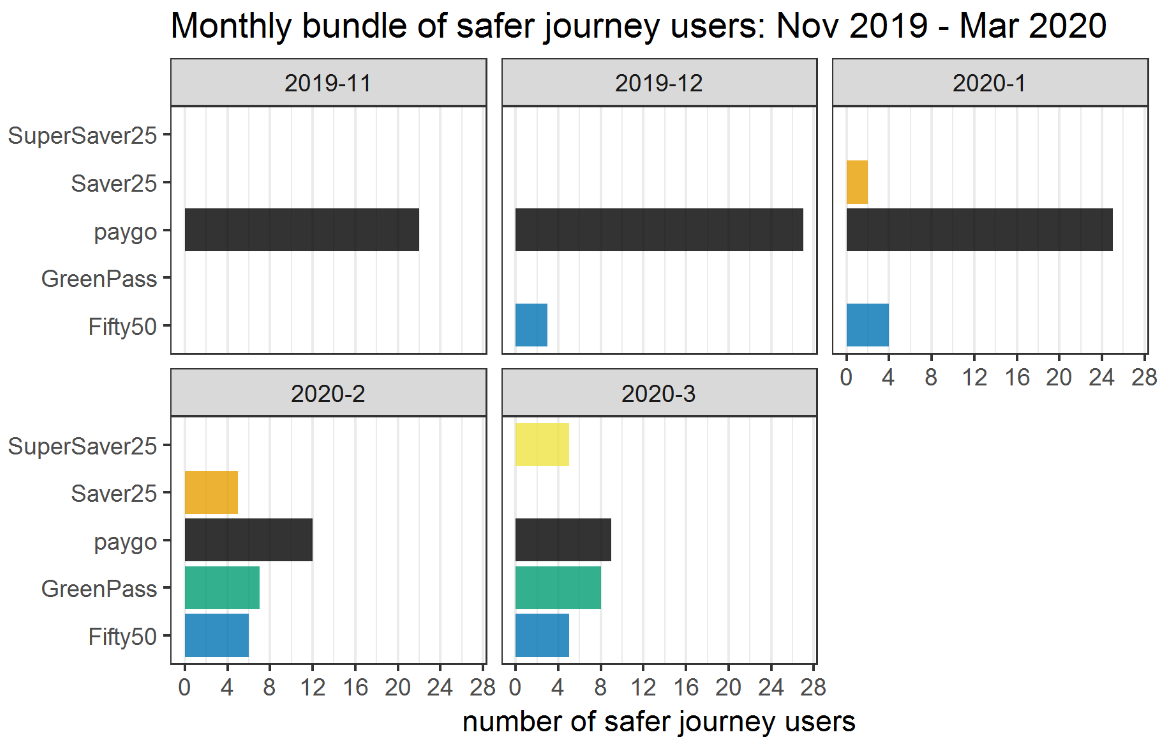

Figure 3. A High level summary of the absolute bundle uptake by month for Safer Journey's participants

The evidence on the acceptance of monthly bundles is very encouraging, with the 91.9% for PAYG in December dropping to 81.6% in January and then 44.7% in February before increasing marginally to 46.2% in March. In the final month when all bundles are available (although SuperSaver25 replaced Saver25), we have a bundle take up of 53.8%[6]. The percentages for each bundle in March are 12.8%, 12.8% and 28.2% respectively for Fifty50, SuperSaver25 and GreenPass. This aggregate share from real preference evidence is within the range of what has been found in stated preference studies (30%-55%) such as Ho et al. (2018) and is the first tangible evidence of the external validity, at least at an aggregate level, of the stated preference survey responses[7]. What we are seeing is some learning of bundle experience, in part influenced by changing monthly travel needs. Given the sample size, however, care is taken in generalising this evidence.

[6] This compares with 36.5 percent for all trial participants.

[7] We must recognise that studies such as Ho et al. (2018) include respondents who do not have access to a car, and so a direct comparison of samples must be cautioned.

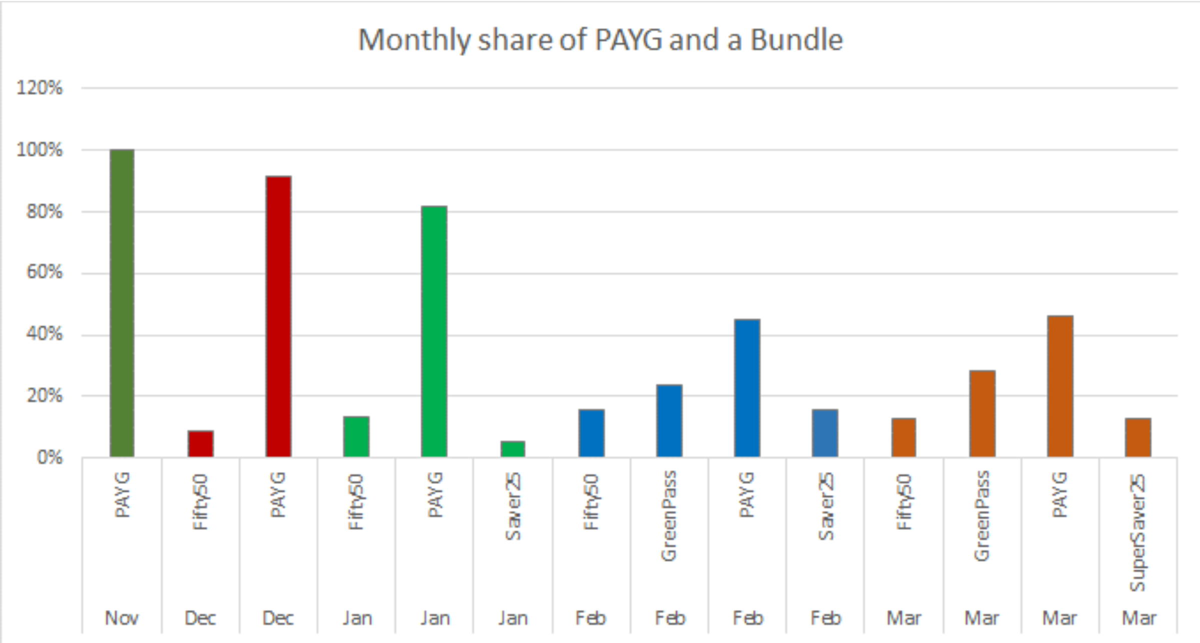

Figure 4. The percentage distribution of PAYG and bundles subscription for each month (note: each month sums to 100%)

Figure 5 shows the monthly car kilometres at the participant level and the monthly bundle they were on for each month. Figure 5 also identifies, on the x-axis, the month each safer journey user joined the MaaS trial and the month they left the trials[8]. On the other hand, the vertical axis shows private car kms travelled on a log10 scale while the colours identify the participant's mobility agreement, be it a PAYG user or a monthly subscriber. Overall, a lot of variation in monthly car kilometres can be observed at the individual level, with December being most substantial. This is expected in the holiday season when many travellers would typically use car more, especially for longer road trips (e.g., P042 drove from Sydney to Melbourne and back) or do not use their private car at all (e.g., P178, P082).

Without an intervention of monthly mobility bundles, car use after the holiday season was expected to go back to normal, and the total kms travelled in January and February 2020 should be comparable with that in November 2019 for PAYG users. This expectation is observed in several PAYG participants such as P002, P004, P007 (see Figure 5). After taking up a bundle, these participants appear to reduce their monthly car kilometres, while very little change in monthly car kilometres was observed for those who continued to use MaaS as a PAYG user (P031, P099, P173). While month-to-month variation in car kilometres is an issue that needs to be acknowledged in this descriptive analysis, the evidence is that MaaS subscriber's car kilometres in February are generally much lower than those individuals who continued with PAYG. The average kilometres for February are 658, 266, 477 and 222 respectively for PAYG, Fifty50, Saver25 and GreenPass (an average of 284 kilometres for the all three bundle subscribers). This is a very important result suggesting that MaaS bundles do attract interest by active car users, and that these appear to be participants who rely less on the car for their mobility needs. We are not, however, able to conclude that subscription to a MaaS bundle has reduced car kilometres compared to what car usage would have been if the bundle subscription was not available. The only months that have similar periods for travel activity comparison, that are not a special month like

[8] Two participants resigned their position at IAG during the trial and hence they were required to leave the trial.

December and January[9], are October and November, where the average monthly kilometres are respectively 513 and 474, still much more than the average of 284 for the bundle subscribers in February. In the formal modelling below, we investigate this matter.

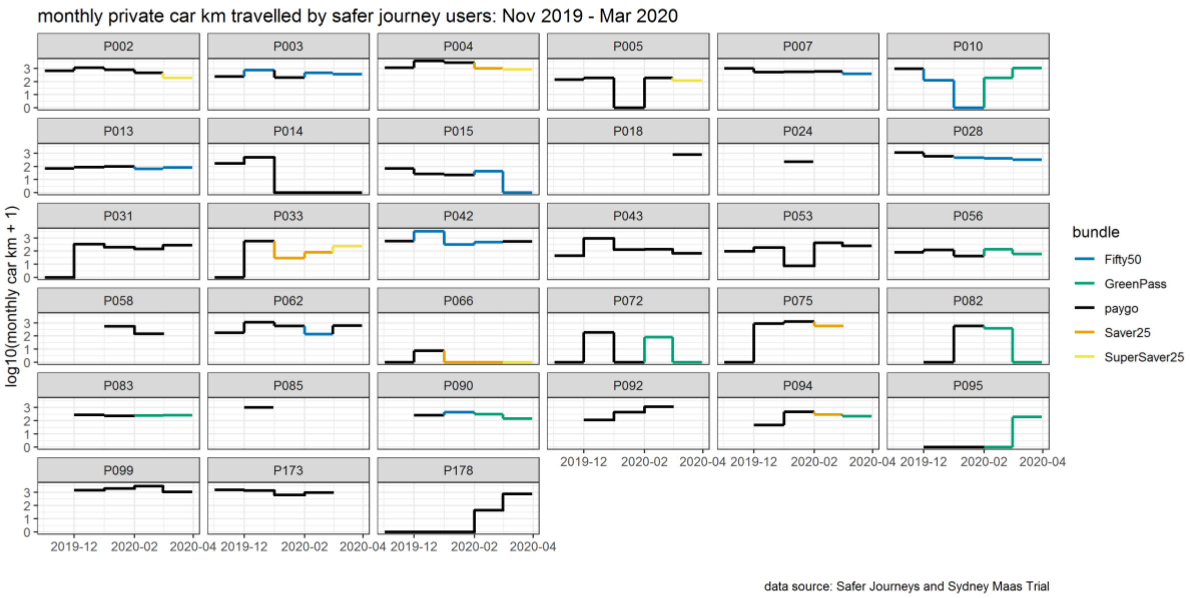

Figure 5. Profile of monthly car kilometres travelled by Safer Journey users in the Sydney MaaS trial

Model Results for Trial Months with Mobility Bundles

The model system estimated for the choice between PAYG and a bundle, as well as monthly car kilometres, considered a number of variables that describe the socioeconomic status of the participants, the incentives offered with each bundle including the change in the metric for ride share (from a percentage to dollars) and the amount of money saved per month compared with PAYG. Table 1 summarises the data items that were considered in various models, resulting in the preferred model summarised in Table 2. Specifically, we found that a series of dummy variables associated with each specific bundle and the associated trial month (e.g., December Fifty50 bundle), relative to PAYG, did not provide as good a behaviourally and statistically significant explanation of the choice between PAYG and bundles in contrast to modal trip activity by each mode during the trial, month-specific dummy variables, estimated financial savings each month associated with bundle selection,[10] and socioeconomic characteristics.

[9] In Australia, December is very much a party month with an elevated use of rideshare, and January is the main holiday month with reduced metropolitan travel (hence local public transport) and increased use of air and car for long distance travel.

[10] Defined as the estimated saving associated with a subscribed bundle (i.e., the bundle the participant actually subscribed to for that month) compared to the cost outlay under PAYG. A negative value indicates that the subscribed bundle is more expensive than PAYG, and a positive estimate indicates a saving. We set PAYG to $0.

Table 1. Descriptive Statistics of Data (Sample size = 171 participant months)

Variable	Units	Mean (standard deviation)	Range (min, max)
Monthly kilometres	kilometres	433.9 (587)	6.5, 3708
Pay as you go	proportion	0.651	0,1
Fifty50 bundle	1,0 (Dec-Mar)	0.127	0,1
Saver25 bundle	1,0 (Jan-Feb)	0.054	0,1
SuperSaver25 bundle	1,0 (March 1-20)	0.033	0,1
Green Pass	1,0 (Feb-March 1-20)	0.134	0,1
Gender	Male = 1, Female = 0	0.597	0,1
Age	Years	40.87 (8.54)	30,60
Adults in household	Number	2.27 (0.76)	1,5
Children in household	Number	1.13 (0.84)	0,2
Car licenced drivers in household	Number	2.13 (0.70)	1,5
Number of cars in household	Number	1.62 (0.75)	1,4
Access to a car	Access to a car = 1	0.893	0,1
Subscribe to a bundle	1,0	0.349	0,1
Sample month participation - December	1,0	0.228	0,1
Sample month participation - January	1,0	0.255	0,1
Sample month participation - February	1,0	0.255	0,1
Sample month participation - March	1,0	0.262	0,1
December Fifty50 bundle	1,0	0.022	0,1
January Fifty50 bundle	1,0	0.034	0.1
February Fifty50 bundle	1,0	0.040	0.1
March Fifty50 bundle	1,0	0.034	0,1
January Saver25	1,0	0.013	0,1
February Saver25	1,0	0.040	0,1
February GreenPass	1,0	0.060	0,1
March GreenPass	1,0	0.074	0,1
March SuperSaver25	1,0	0.033	0,1
Weekly modal travel activity:			
Car driver trips	Number	44.13 (29.4)	2,131
Car passenger trips	Number	0.041 (0.26)	0,2
Public transport trips	Number	22.59 (16.19)	2,76
Rideshare (taxi and Uber) trips	Number	3.31 (4.11)	1,25
Estimated monthly financial saving on the subscribed bundle compared to PAYG	$ per month	6.97 (16.42)	-28,72
Subscription bundle fee and discounts:			
Subscription fee	$ per month	25.33 (42.91)	0,125
Public transport discount	%	21.44 (35.25)	0,100
Ride share discount	$	0.483	0, 3
Ride Share discount	%	1.933	0,15
Car share discount	%	0.805	0,15

In estimating the models, given that the unit of analysis is a participant month and there is more than one observation per participant, the data structure is like a panel (repeated observations for each respondent) and hence there exist observations in a group that are likely to be correlated through common latent heterogeneity across four months. This sequential time period of data, defined by the month, is accommodated through a cluster algorithm (Greene 2000) that is similar to a random effect. The parameter estimator is unchanged, but an adjustment is made to the estimated asymptotic covariance matrix (see Greene 2017) to correct the standard errors. We tested for fixed and random effects; however, the fixed effect model did not work due to sample size, and the random effects model failed to converge. A random parameter form (normally distributed) for monthly kilometres was investigated, but it was found to be statistically non-significant due, we suspect again, to sample size.

Table 2. Model results

	Parameter estimates	Clustered standard errors	z-value
Discrete Choice: Binary Logit Bundle (1) vs PAYG (0)			
Constant	-0.7098	3.272	-0.22
February dummy variable (1,0)	2.2856	0.943	2.42
March dummy variable (1,0)	2.7440	1.277	2.15
Monthly car passenger trips	-28.096	2.354	-11.93
Monthly public transport trips	0.0702	0.019	3.57
Monthly savings in costs for a bundle cf. PAYG (log$)	41.572	1.203	34.57
Male (1,0)	-1.7499	0.962	-1.82
Car licenced drivers in household	-3.7002	2.261	-1.64
Restricted log likelihood	*-22.170*		
Pseudo R_2	*0.780*		
Continuous model of Monthly Car Kilometres: Poisson model with normal heterogeneity			
Constant	6.1751	0.0272	227.3
Access to a car (1,0)	1.1223	0.0209	53.52
Age of participant (years)	-0.0339	0.00052	-43.72
Gender of Male (1,0)	-0.2834	0.0088	-32.38
Number of children in household	0.1174	0.0055	21.44
Predicted probability of choosing a monthly bundle	-0.6690	0.0114	-60.05
Sigma	0.584	0.012	47.90
Log likelihood	*-36,637.4*		
Pseudo R_2	*0.134*		
Vuong statistic vs Poisson (favours the extended model)	*6.147*		

The Choice between take up of a bundle and PAYG

We begin by discussing the binary choice logit model. The overall goodness of fit is very impressive with a pseudo R_2 of 0.780. Except for the two socioeconomic characteristics (male and number of licensed car drivers in a household) and the constant, the variables are statistically significant at the 95 percent level of confidence. The socioeconomic characteristics are statistically significant at a slightly lower level of statistical confidence.

Initially, we had anticipated that we might be able to introduce a series of variables to represent the subscription fee and the mode-specific discounts, since although they do not vary within a particular bundle offer, they do vary across the offered bundles. However, these variables are highly correlated and result in a very unstable bundle choice model. The amount of variance is not sufficient to capture the role of such discounts, and indeed is a reason why revealed preference data like that in the trial creates challenges in model estimation, and is one of the justifications why stated preference data is appealing. Until there is sufficient variation in the incentives and subscription fees associated with real market offerings of MaaS bundles, there will be limitations to using such data in studying bundle choice. This may require the pooling of many MaaS products to be able to obtain sufficient variation. However, we found that the variation in the financial savings associated with each bundle (Table 1) relative to PAYG for each participant, enables this influence to be tested. All other influences remaining constant, we find that as the financial savings increase, the probability of choosing a bundle increases. The extent of the change is presented below as a semi-elasticity.

Two dummy variables for the months of February and March were statistically significant and positive. What this suggests, and reaffirms what we know about take up of bundles as we offer additional bundles in a monthly sequence, is that relative to the previous months of December and January, the probability of choosing a bundle increases as we move monthly through the trial. This is very reassuring and supports the way in which we assessed new bundles given the experience with previously introduced bundles. The way the trial was designed provides strong clues as to how bundles can be designed through time. A caveat must be mentioned, namely Covid-19, which has had a massive impact on travel in general after March 12[11], with the greatest impact on public transport and ride share patronage (Beck and Hensher 2020). Car use has continued, but in general it also dropped (see Figure 5). What we can say, however, is that car use was greater in December and January than in February and March up to the 12th March.

Finally, we found that two socioeconomic characteristics, gender and the number of licensed drivers in a household, were statistically significant negative influences on the probability of choosing a bundle, suggesting that male participants and those in households with more driving licences are less likely, holding all other influences constant, to choose a bundle over PAYG. The other socioeconomic characteristics in Table 1 were not found to be statistically significant.

Care must be taken in interpreting the numerical magnitude of each parameter estimate since they are non-comparable in this logit non-linear form, and hence below we present partial effects and elasticities as a way of meaningfully comparing the impacts of each bundle component. The behavioural sensitivity of the probability of choosing a bundle compared to PAYG for each of the explanatory variables can be given by an elasticity and a partial effects indicator. For the logit form, the elasticity of the probability is given in equation (6) and the partial (or marginal) effect in equation (7).

$$\frac{\partial \log E(y \mid x)}{\partial \log x_k} = \frac{x_k}{E(y \mid x)} \cdot \frac{\partial E(y \mid x)}{\partial x_k} = \frac{x_k}{E(y \mid x)} \cdot \text{marginal effect} \tag{6}$$

$$\frac{\partial E(y|x)}{\partial x} = \frac{\partial F(\beta' x)}{\partial x} = \frac{dF(\beta' x)}{d(\beta' x)} \beta = F'(\beta' x)\beta = \mathrm{f}(\beta' x)\beta \tag{7}$$

The direct elasticity of the probability of choosing a bundle compared to PAYG with respect to the number of monthly public transport trips is 0.820 (with a t-value of 3.86 and a 95 percent confidence interval of 0.042 to 1.24 using the Delta method). The direct elasticity of the probability of choosing a bundle compared to PAYG with respect to the number of monthly car passenger trips is -1.25 (with a t-value of 3.38 and a 95 percent confidence interval of -1.978 to -0.527). Thus, all other influences remaining unchanged, a one percent decrease in monthly car passenger trips will result in a 1.25 percent increase in the probability of choosing a bundle over PAYG; and for public transport trips a one percent increase in monthly public transport trips will result in a 0.820 percent increase in the probability of choosing a bundle over PAYG. As an example, if we work with the average bundle choice share of 0.349 (Table 1) and if we can achieve a 10 percent increase, on average, in monthly public transport trips, then we predict an increase in the probability of choosing a bundle of 8.2 percent, or an increase from 0.349 to 0.378. The equivalent change for a reduction in car passenger trips is 12.5 percent or an increase to 0.393. If this evidence was scalable, given the mix of MaaS bundles offered in the trial, we can expect a significant improvement in traffic congestion if we are able to reduce car kilometres by 6 to 10 percent, which is equivalent to returning the road environment to school holiday levels of congestion.

[11] On March 12, all participants as employees of IAG were advised to work at home where possible and all non-local domestic and international travel was to cease, which aligned with the Stage 2 restrictions imposed on Society on March 20 (Beck and Hensher 2020).

For the average monthly financial savings, since it is transformed as a natural logarithm, we have to use a semi-elasticity formula (equation 8), interpreted as the change in probability for a 1% change in x. That is, a semi elasticity formula measures the relationship between a percentage change in X and an *absolute* (not percentage) change in Y, and hence we refer to a unit increase in the explanatory variable (not percentage, but change in percentage points).

$$\frac{\Delta \text{Prob}}{100 * \dfrac{\Delta x}{x}} = \frac{\beta \text{Prob}(1 - \text{Prob})}{100} \tag{8}$$

The model obtains a semi-elasticity of 1.853 (t value of 4.4) for average monthly financial savings relative to PAYG. A 1 percent change in the average monthly financial savings will result in a 1.853 change in the probability of choosing a bundle over PAYG. The average change in the probability of choosing a bundle when the average savings increases by 10% (noting a change in the log of .1 is about a 10% increase in the average savings), is .185 or 18.5 probability of bundle choice points. Thus, given the average bundle choice share of 0.349, this equates to a probability of bundle choice of 0.414 (= 0.349 × 1.853) for an additional 10 percent financial savings over PAYG.

For the remaining variables, we have calculated the partial or marginal effects. The average marginal effect provides an effect on the probability. It is the average change in the probability when an explanatory variable increases by one unit. When a variable is a dummy variable, we have to take the exponential. The marginal effect parameters (with t values in brackets) for the February dummy, the March dummy, male, and number of household members with a driver licence are respectively 0.129 (3.83), 0.177 (2.61), -0.076 (1.56) and -0.289 (1.12). For example, for the February dummy variable influence, we obtain exp(0.1294)=1.138 suggesting that we are 11.38% more likely to choose a bundle in February compared to December and January; the equivalent percentage for March is exp(0.177)=1.194 or 11.94% more likely to choose a bundle in March compared to December and January. The main implication of all of these findings is that they provide suggestions for ways of harnessing MaaS as a policy instrument supporting sustainable transport outcomes.

The Relationship between monthly private car kilometres and bundle take up

Turning to the Poisson regression model (in Table 2), with monthly kilometres defined as an integer for the Poisson count model, the overall goodness of fit (as pseudo R_2) is 0.134. The tau (τ) parameter (equation 5) associated with the zero inflated Poisson model with normal heterogeneity was not statistically significant and so we opted for the Poisson model with normal heterogeneity, where the sigma (σ) parameter, the standard deviation of heterogeneity, is statistically significant at the 1 percent level. The Vuong statistic of 6.147 suggests that the estimated extended Poisson model in Table 2 is favoured over an unaltered Poisson model.

Four socioeconomic characteristics have a statistically significant influence on monthly car kilometres, namely access to a car, participant age, gender, and the number of children in the household. All other influences remaining constant, having an access to a private car increases monthly car kilometres, but older participants tend to drive less than younger participants, with male respondents having fewer monthly car kilometres than female participants. Households with more children tend to use their cars much more, as might be expected. These findings are sample-specific and so cannot be generalised, although it does suggest that there are socioeconomic segments associated with car use which translates into differences in the propensity to take up a bundle compared with PAYG if someone decides to participate in MaaS.

Finally, we have included the predicted bundle choice as a probability measure obtained from the binary logit model of bundle vs PAYG. It is a statistically significant and negative effect which indicates that, *ceteris paribus*, if the probability of choosing a bundle increases, then there is an expected reduction in monthly car kilometres. The parameter estimates of a Poisson regression may be interpreted as semi-elasticities as discussed above in equation 8.[12] The parameter of -0.669 for the probability of choosing a bundle indicates that, ceteris paribus, if we increase the probability by 1 percent, we expect to have a 66.9 absolute reduction in monthly car kilometres. At the mean monthly kilometres of 434, a 1 percent increase in the probability of choosing a bundle (from 0.349 to 0.353) is predicted to reduce monthly kilometres from 434 to 367 kilometres. If scalable over a large population of MaaS subscribers, this is a significant reduction in car kilometres. The partial effect and hence semi-elasticity increases at a decreasing rate as the probability of choosing a bundle increases, although the deviation from a linear effect is small.

The overall findings reinforce a position that a well-designed suite of subscription plans under MaaS can influence the use the car in a positive and sustainable way, contributing to a reduction in emissions.

Conclusions

Part of the remit for MaaS is to offer a more attractive way for individuals (and groups of any denomination) to be better informed about mobility options. This in turn opens up opportunities to encourage changes to travel behaviour that not only provide direct benefits to the travelling public, but also support achieving broader societal goals. It is these societal goals that are increasingly being promoted through what many governments are calling mobility frameworks (Hensher et al. 2020). One of the overarching themes in the MaaS ecosystem is the desire to reduce private car use, and as a consequence contribute to the reduction in emissions and other negative externalities such as traffic congestion.

The Sydney MaaS trial is well placed to investigate how MaaS may appeal to these personal and societal agendas. In this paper, we have focussed on the trial activities of the sub sample who have provided data on their car use over the months in which subscription bundles have been offered, starting with a single bundle in the first month after a PAYG familiarisation period with the digital platform (the *Tripi* App), and then incrementally adding a bundle each month. The sequential enhancement of bundles offers an innovative way of learning by doing with a sample of participants, such that the opportunity to grow interest in a bundle may be increased through analysis of each months travel activity and bundle choices. This was indeed an appropriate strategy since it resulted in a slow but noticeable move away from PAYG to bundles (see Figures 3 and 4), even if PAYG remained the dominant way[13] of using *Tripi* and participating in the trial.

With the growing preferences favouring specific bundles, we wanted to know if there was an impact on monthly car use, and what features of the bundles in particular might be the main triggers for changing patterns of car use. Using a joint discrete and continuous choice model system to study the influences on the choice between a bundle and PAYG (the discrete choice model), and the influences on monthly private car kilometres (the count model), we have been able to show that a subscription to a monthly mobility bundle does influence monthly car use in a statistically significant way.

Importantly, it is the combination of a subscription fee and a suite of mode-specific financial discounts that will ultimately determine the appeal of MaaS bundles and indeed Maas more generally. We would argue that having monthly mobility bundles for subscription will be the key influence on whether MaaS is to grow in a scalable way or remain a niche construct. Without subscription options, MaaS seems be nothing more than a potentially attractive trip planner which may change travel behaviour to some

[12] Suppose x is not a log variable, then β associated with x can be interpreted as a semi-elasticity, meaning that a one unit change in x will change $E[y|\mathbf{x}]$ by 100β (Wooldridge 2002).
[13] Especially for all trial participants and not just the Safer Journeys participants.

degree as a result of better information, but there is no guarantee. A qualitative survey with 22 sampled trial participants, which were conducted in the middle of the trial to gather qualitative evidence for monthly bundle design, suggests that a few individuals are looking for a limited multimodal subscription plan (maybe two or three modes at the most), and that a digital platform under PAYG alone is unlikely to be of much interest to the majority of improved mobility aspirants. It is evidenced that money talks loudly, despite the added recognition of the importance of good quality public transport and rideshare services, in terms of convenience, reliability, safety, transfers and travel times. Thus, without financial incentives, especially where there are no service enhancements only available to MaaS subscribers[14], the likelihood of MaaS achieving noticeable outcomes aligned with sustainability objectives may be unlikely to be achieved.

This then is the challenge going forward for prospective commercial MaaS products. What subscription plans will attract users, how will the financial incentives be funded, and can we deliver a digital platform that is sufficiently multimodal, easy to use, and providing information of the users travel activity that can inform their future choices in a way that has private and social benefits? The current paper has shown, through the Sydney trial, that there is an appetite for such a product, and that it can contribute to achieving sustainability goals; however, a lot of ongoing research is required to integrate the constituent parts and feature a business case that is attractive to both private interests, users and government. The trial has indeed commenced that journey, although the Covid-19 pandemic may require new initiatives in order to preserve and grow the appeal of MaaS, at least in the short to medium term when the popularity of the car is likely to escalate as a response to biosecurity in contrast to the use the shared modes, public transport and rideshare.

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[14] Mobility mode providers have shown no interest to date in offering service enhancements that are only available to MaaS subscribers; and hence financial incentives are the only levers available unless non transport services such a retail can offer MaaS bundle specific rewards, something we suggest will be necessary to support a business model and commercial case. The idea of multimodality should then be read as multiservice MaaS.

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