Estimating values of time from revealed preference data

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1.0 Introduction

Values of time (VOTs), i.e. the trade-off ratios between travel time and travel cost, play a key role in the modelling and appraisal of transport schemes and policies.

As Hess et al. (2020) note, while the early VOT studies in the 1960s and 1970s were based on revealed preference (RP) data capturing mode choices observed in the real world, current standard practice in Northern Europe (including the UK) is for the analysis of simple time-cost trade-offs collected using stated preference (SP) data.

In a UK context, the use of SP data for national VOT estimation dates back to the national VOT study reported on in 1987. In that study it was argued that SP data gave acceptable error margins for VTT estimates from sample sizes that were feasible for the budgets available (Hess et al, 2020). An important advantage of SP data over RP is that the collection of multiple choices from each individual means that it is a cost effective form of data collection, and SP methods have been used for national VOT estimation in the UK since the 1987 study.

However, while SP methods currently dominate VOT estimation some researchers have suggested that it is worth re-considering the use of RP data, in part because large RP datasets now exist, and in part because of some the complications involved in analysing hypothetical SP choices (Daly *et al*, 2014).

This paper does not attempt to present a comprehensive review of the literature on SP and RP VOT estimation methods. Instead it presents a comparison of a series of UK VOTs estimated from RP data to comparable values estimated from UK SP data. It then presents in more depth a recent study that estimated Irish VOTs from RP data, and then compared these to values obtained by transferring the latest UK VOT models to Ireland.

The motivation for these comparisons is to explore the extent to which RP data can be used to identify reasonable VOTs, and where it is possible to estimate RP VOTs to explore the degree of consistency or otherwise with SP values.

Section 2 of this note introduces the RP estimation approach and discusses some of its strengths and weaknesses. Section 3 summarises UK evidence that has compared RP and SP VOT estimates. Section 4 presents the Irish VOT estimations and compares the results to those obtained by transferring the latest UK VOT models to Ireland. The note concludes in Section 5 with a summary and recommendations.

2.0 RP estimation approach

2.1 Estimating VOTs from mode-destination models

This section explains how VOTs can be identified from results of mode-destination models that represent in-vehicle time and monetary cost separately in the utility functions. Note that this approach cannot be used for models that used a generalised time formulation as in these models VOTs form an *input* to the model estimation process[1].

The utility functions for the mode-destination alternatives include in-vehicle time terms by mode, monetary cost terms and other terms including socio-economic terms, mode constants and any destination constants. For illustrative purposes we assume that cost enters the utility function in both linear and log-cost forms drawing on the work of Fox *et al.* (2009), as such the model specification incorporates ‘cost damping’ whereby the marginal impact of cost reduces as cost increases.

$$U^{m,d} = \beta_{IVT}^{m} IVT^{m,d} + \beta_{Cost} Cost^{m,d} + \beta_{LogCost} \ln(Cost^{m,d}) + ... \quad (2.1)$$

Where: $U^{m,d}$ is the utility of the alternative defined by mode *m* and destination *d*

β_{IVT}^{m} is the in-vehicle time parameter for mode *m*

$IVT^{m,d}$ is the in-vehicle time by mode *m* to destination *d*

β_{Cost} is the (linear) cost sensitivity parameter for mode *m*

$Cost^{m,d}$ is the cost by mode *m* to destination *d*

$\beta_{LogCost}$ is the log cost sensitivity parameter for mode *m*

$\ln(Cost^{m,d})$ is the log of cost by mode *m* to destination *d*

... are other terms in the utility function[2].

The implied VOTs can then be calculated as follows:

$$VOT = \frac{\partial U / \partial time}{\partial U / \partial cost} = \frac{\beta_{IVT}^{m}}{\beta_{Cost} + \dfrac{\beta_{LogCost}}{Cost^{m,d}}} \quad (2.2)$$

If the log-cost term is not identified then the VOT equation reduces to the ratios of the IVT and cost terms, as such a single VOT value is identified for each mode.

However, if the log-cost term is identified then the VOTs vary as a function of the cost of the journey. Provided all parameter estimates are negative then then the VOTs will increase with distance. In order to calculate representative average VOTs for each mode average cost values are required. As cost distributions tend to be right skewed the medians rather than means are usually used to calculate average cost values.

2.2 Strengths and weaknesses of the RP estimation approach

The key advantage of the RP estimation approach is that it uses choices revealed in a real market whereas in SP experiments respondents are asked to respond to hypothetical choices

[1] Specifically in generalised time models monetary costs are divided by VOTs in order to convert them into generalised time minutes. The sensitivity to generalised time changes is then estimated.

[2] Note that these other terms include other level-of-service terms such as walk and wait times. Equation (2.1) only presents those terms used in the VOT calculation given in Equation (2.2).

and those choices may be subject to bias. If RP data already exists with sufficient sample sizes to enable models to be estimated then it is potentially a cost-effective option for VOT estimation, for example countries where there is existing national travel survey data.

The key disadvantage of RP data is that while it uses real choices these are combined with *modelled* network information on times, costs etc. as well as a series of assumptions about public transport fares, fuel costs, parking costs and so on in order to determine modelled costs by mode. Thus while the choices are observed the costs are subject to error and potentially bias. These issues were recently explored by Varela *et al.* (2018) who found that measurement errors in network models for commuter models in Stockholm to be larger for travel cost than for travel time.

It should be emphasised that in the RP mode-destination models referenced in Section 3 the primary objective was to estimate models of mode-destination choice suitable for forecasting demand under a range of different policies. The VOTs implied from the ratios of the in-vehicle time and cost parameters were one validation criterion considered alongside other criteria including overall fit to the observed mode-destination choices and model elasticities.

However, by improving the modelled cost and time information it would be possible to use RP data in a study focussed on VOT estimation. For example, self-reported cost and time information could be collected for the chosen journey and compared to the modelled costs and times for that journey to inform changes to all the modelled times and times.

3.0 Comparison of UK RP and SP VOTs

This section starts by presenting the results from a UK meta-analysis study that provides insight into differences between RP and SP VOTs. It then discusses results from two recent UK studies that have compared RP VOTs from mode-destination models to the TAG guidance VOTs that were derived from SP data.

The TAG guidance VOTs are calculating using the SP models from the Arup *et al.* (2015) study. To determine nationally representative VOT values for guidance the SP models were applied to a sample of trips from the National Travel Survey (NTS) data. Two sets of VOT values were determined, distance weighted values for use in appraisal (given in the TAG workbook) and trip-weighted average values for use in modelling (given in TAG Unit M2.1). The comparisons made in Sections 3.2 and 3.2 are to the trip-weighted VOTs.

3.1 UK meta-analysis

Abrantes and Wardman (2011) undertook a meta-analysis of UK values of travel time. Their data spanned the 1960 to 2008 period, and it is noteworthy that for the 1960-1979 period 92% of the studies included used RP data, in the most recent 2005-2008 period just 13% of the 243 studies used RP illustrating the current preference for SP data for VOT estimation.

In total their study included 31 RP studies and 212 SP studies. From these studies they estimated a meta-model that gives the average VOT values according to the characteristics of the study and the trip. These characteristics includes in-vehicle time versus wait or walk tine, income, distance, journey purpose, mode, SP presentation, fuel or toll cost, and importantly in the context of this paper whether the study used RP data.

The results from their meta-model indicate the values of in-vehicle time identified from RP data to be 22% higher on average than those identified from SP data. The regional terms also indicated that travellers in London and the South East have valuations 27% higher than those in the rest of the UK, the study authors suggested this will reflect higher average incomes and potentially also the impact of more crowded and congested travel conditions.

3.2 Model of Travel in London

MoTiON (Model of Travel in London) includes mode-destination models that were estimated from RP data, specifically London Travel Diary Study (LTDS) data from 2015/16–2017/18. When the mode-destination models were validated the average VOTs were compared to those in TAG guidance which are derived from the 2014 UK VOT study models (Arup et al. 2015).

Mode-destination models were estimated from six home-based and eight non-home-based models (Fox and Patruni, 2020). The definitions of the non-home-based models is complex, furthermore these trips are shorted on average. Therefore these comparisons have focussed on the eight home-based purposes:

1. Commute
2. Business
3. Primary education
4. Secondary education
5. Tertiary education
6. Shopping
7. Escort
8. Other travel.

For primary education and secondary education no cost information is represented as PT fares are zero for education travel in London and it is assumed parents pay for the cost of escorting children to school by car.

In these mode-destination models, in-vehicle time parameters are estimated for car, train and bus modes. Separate monetary cost parameters are also estimated, in most cases incorporating cost damping so that the marginal sensitivity to costs decreases with increasing cost. The implied VOTs are then calculated from the in-vehicle time and cost parameters, in models with cost damping the VOTs increase with the cost of the journey and this means that the implied VOTs are a function of cost.

For commute, cost sensitivity parameters were estimated for three household bands and so mean VOTs were calculated by income band for comparison to the TAG VOTs. The MoTiON VOTs are weighted averages over modes.

Table 1: MoTiON commute VOTs

Household income band	VOT (£/hr) 2014 prices and values
<£25k	6.21
£25-50k	9.61
£50k plus	13.91
TAG	8.44

Noting that the TAG value corresponds to an average household income of £57,852 it can be seen that MoTiON VOTs are significantly higher than the TAG values. This may in part reflect higher levels of congestion and crowding for London commuters compared to the UK average.

For (employer's) business there is no income segmentation.

Table 2: MoTiON business VOTs

VOT value	VOT (£/hr) 2014 prices and values
MoTiON	13.13
TAG	12.46

The MoTiON business VOT is just 5% higher than the corresponding TAG value.

For the remaining four home-based purposes (tertiary education, shopping, escort and other travel) it was not possible to estimated acceptable cost sensitivity parameters. These models tended to have cost sensitivities that were too low and associated with this implied VOTs that were too high. Therefore cost sensitivity information was transferred from other sources for these purposes (see Fox and Patruni 2021 for more details).

These difficulties highlight some of the limitations of the RP estimation approach, namely issues associated with high positive correlations between costs and in-vehicle times and the fact that some travellers may prefer a more expensive alternative (in particular retired persons who drve despite the availability of a free PT alternative contributed to weak cost parameters for some purposes).

3.3 National Transport Model

For version 5 of the National Transport Model (NTM v5) RP mode-destination models were estimated from National Travel Survey (NTS) data collected between 2010 and 2015. These estimations are complete but the final reports have not been published yet, therefore this section discusses the comparison of the RP VOTs to the SP values in TAG but does not present the VOT values.

For commute the RP VOTs were around one-third higher than the TAG SP value whereas for business the RP values were around 45% higher than the corresponding TAG SP value. By contrast for education the two sets of values matched more closely with the RP value within 10% of the SP value.

NTM uses a detailed segmentation of discretionary travel, with separate shopping & personal business, recreation and leisure, and holiday & day trip purposes. For these the pattern was mixed, with an excellent match between RP and SP values for shopping & personal business, a close to 50% over-prediction for recreation and leisure and a larger still over-prediction for holiday & day trip. However, the higher VOTs for holiday & day trip are consistent with the significantly higher mean trip lengths for this sub-purpose relative to other trips as a whole.

Overall the RP and SP values are broadly comparable but the general tendency is for the RP values to be higher than the corresponding SP values. This is consistent with the MoTiON findings for commute and business travel.

4.0 Comparison of Irish RP VOTs to SP VOTs

4.1 Generating the Irish SP VOTs

In the Irish study there was a need to update the VOTs used in the Irish Department of Transport, Tourism and Sport's (DTTaS) Common Appraisal Framework (CAF). Recent national SP VOT data was not available and so it was decided to transfer the SP VOT models from the 2015 UK study (Arup *et al.*, 2015) to Ireland.

The transfer was undertaken by using a similar sample enumeration approach to that employed in the UK. By applying the UK VOT models to Irish National Household Travel Survey (NHTS) data, Irish VOTs were obtained that take account of differences in the socio-economic characteristics and trip characteristics between the UK NTS and the Irish NHTS. This work is not yet been made publicly available but Table 3 reports the following results from the study which provide comparisons to both the previous CAF values and to the UK TAG values. The percentages that are presented are the differences between the transfer values and the previous CAF and UK TAG VOT values.

Table 3: Transfer of UK VOT models to Ireland (VOTs in 2014 £/hr)

Purpose	Transfer values	Previous CAF values		UK TAG appraisal values	
Commute – all modes	8.98	11.79	-24%	11.21	-20%
Business – all modes		24.39		18.23	54%
Business – car	25.73			16.74	
Other non-work – all modes	2.26		-79%	5.12	-56%

The transferred values for commute are broadly consistent with both the previous CAF values and the UK TAG appraisal values. Median and mean commute trip distances and travel times are significantly lower in the Irish NHTS sample compared to the UK NTS sample and this is consistent with Irish VOTs being one-fifth lower than the UK TAG values.

For business the transferred VOT values are in line with the previous CAF values but over 50% higher than the UK TAG values. This difference has been attributed to differences in incomes between the two samples, in particular the UK values for business use personal income (as that is the income measure used in the SP models) whereas the transfer values may have been made using household incomes which are higher on average[3].

For other, the transferred values are much lower than the previous CAF values but are also less than half the UK TAG appraisal values. Irish trip lengths are shorter than UK values but the extent of the difference between the two sets of values is substantial.

The National Transport Authority (NTA) is a statutory non-commercial body, which operates under the aegis of the DTTaS. Given the low VOT estimate for other non-work the NTA decided to commission a study to provide further evidence around Irish VOT values and the degree of variation between travel purposes. A detailed review of the methodology employed in the SYSTRA / ITS Leeds work was outside the remit of this work, instead the work focussed on providing a set of RP VOTs for comparison to the SP transfer values.

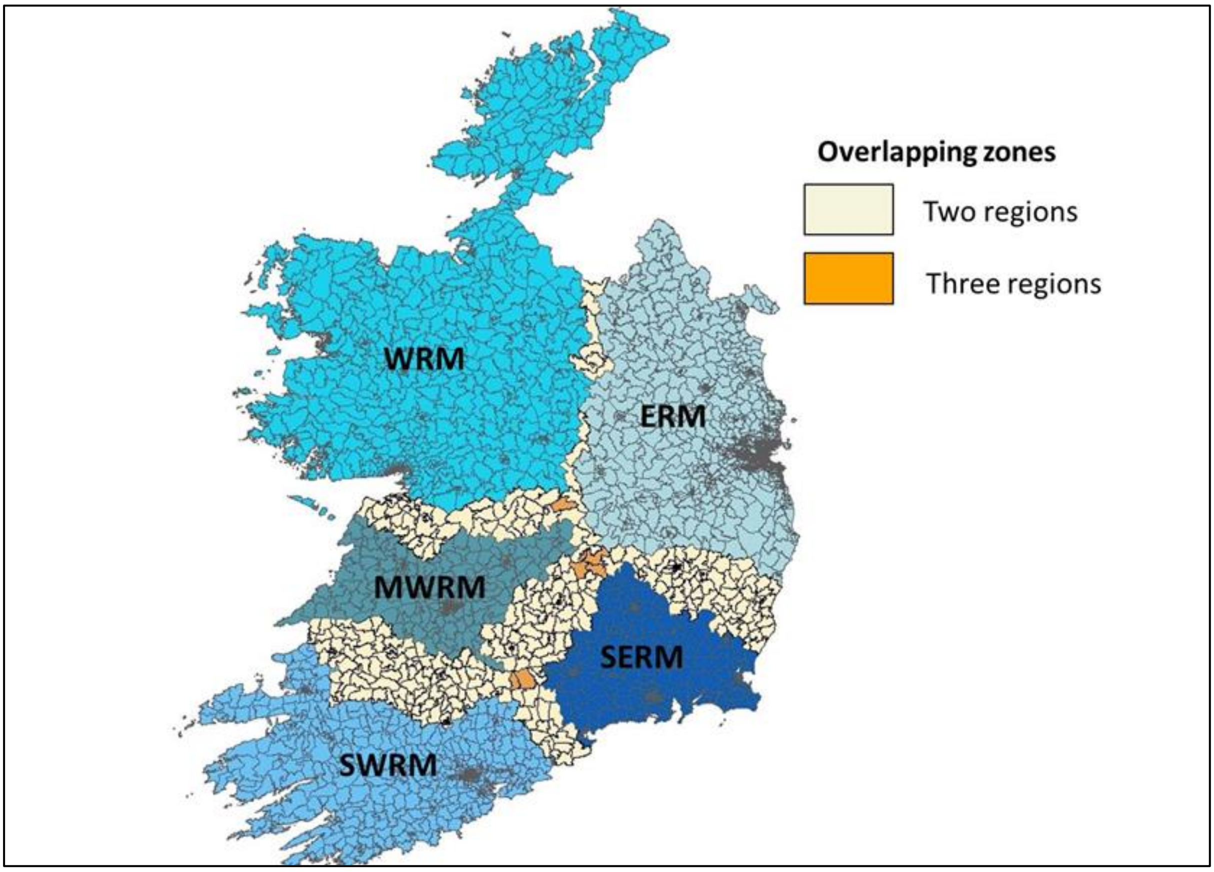
4.2 Model specification

The starting point for this work was existing mode-destination models that have been developed for the Irish Regional Model System (RMS). There are five regions in the RMS that cover the Republic of Ireland, these are illustrated in Figure 1. The five regions have been designed to represent the catchments of the major urban areas and therefore reflect

[3] The Irish NHTS does not collect personal income data.

underlying travel patterns.

Figure 1: RMS regions



Mode-destination modes have been estimated for each of the five regions, however the models have been estimated using a common model specification. It was decided to develop VOT models for the Eastern Regional Model (ERM), this model includes Dublin and the surrounding area and as a result there more significantly more trips made in this region compared to the other four.

In principle data from the five regions could have been pooled and inter-regional trips included[4], however this would have required a considerably larger study and given that the five regions have been specified to the major population centres and their catchment areas lie within a single region then the omission of some long-distance inter-regional trips was judged acceptable.

The starting point for the VOT estimations was the latest mode-destination models estimated for the ERM. These models represent the following modes:

- Car (driver and passenger combined)
- PT (rail, light rail and bus services)
- Walk
- Cycle.

The destination alternatives in the model are the 1907 zones represented in the ERM. As we are modelling mode-destination choice this means that there are 7628 alternatives in the choice set.

[4] In the RMS a separate model is used to forecast inter-regional trips.

A number of steps were followed to convert the existing regional models for the ERM into models suitable for VOT estimation:

- The detailed purposes used in the RMS were aggregated into commute, business and other. Note that education forms part of commute in the UK VOT models and so education was merged into commute rather than other.
- The models were filtered to only include persons aged 18 and above for consistency with the UK VOT models.
- The models were converted from a generalised time specification to use separate cost and in-vehicle time terms as per Equation (2.1).

In the context of VOT estimation the assumptions made around monetary costs are key. For the VOT models car costs per km were taken from the Irish CAF, for commute and other these include fuel costs only.

Parking costs are only defined for a limited number of Dublin city centre zones, however for those zones parking costs can be substantial. Not all travellers who drive into city centres will pay for parking, in fact for zones in Central Dublin it is probable that most people will only travel in if they have free parking available at their destination. To take account of free parking the ERM tour records in the NHTS data were analysed to examine the proportions of people travelling to zones with parking charges who reported that they paid for parking. Parking costs for these zones were then multiplied by these proportions to calculate an average parking cost.

For PT fares, the approach used in the RMS is to create average fares by purpose as a function of average pass ownership levels for each purpose (due to the wider range of possible fare combinations it was not possible to assign an exact fare for each record in a way that is consistent with how the models are applied). However, for VOT estimation we do not need to worry about implementation and using individual-level costs helps ensure the costs for each mode are as representative as possible. Therefore the PT fares were modified to take account of individual pass ownership and in particular that a fraction of travellers have passes which mean they pay zero marginal fare.

4.2 Model results

Table 4 summarises, for each purpose, the sample sizes of tours and the parameters from the model estimations that are used to calculate the implied VOTs using Equation (2.2). The t-ratios for the parameters are presented in brackets.

Table 4: Mode-destination model sample sizes and VOT parameters

	Commute		Business		Other	
Tours		3,161		115		4,706
β_{IVT}^{Car}	-0.0304	(25.6)	-0.0165	(3.1)	-0.0692	(21.9)
β_{IVT}^{PT}	-0.0112	(7.6)	-0.0302	(3.3)	-0.0266	(12.6)
β_{Cost}	-0.0015	(12.0)				
$\beta_{LogCost}$			-0.6125	(3.6)	-0.4983	(10.6)

For commute the best model has a linear cost specification and so there is no cost damping. The in-vehicle time and cost parameters are all significantly estimated.

For business the best model has a log cost specification which gives a strong cost damping effect. All three in-vehicle time and cost parameters are significant at a 95% confidence level but the significance of the estimates is not particularly strong, a consequence of the small sample size. It is noted that there were just 12 PT tours in the estimation sample.

For other the best model also had a log cost specification which gives a strong cost damping effect. Estimating the cost sensitivity parameters for other was problematic despite the large sample sizes, this was in part related to a significant fraction of tours made by persons with PT passes where the marginal cost of a trip is zero once the pass is owned. Some of these people choose to drive (with an associated cost) and this causes the cost parameter to weaken. This in turn had implications for the implied VOTs which are discussed below.

4.3 Values of time

For the commute model no log cost term was identified and therefore the VOTs are constant for each mode, i.e. do not vary as a function of the cost of the tour.

For the business and other models significant log cost terms were identified and therefore the VOTs vary as a function of the tour. Different approaches can be used to calculate the average VOTs by mode, for example using the mean or median costs for the chosen destination alternatives. However, for consistency with the approach used in TAG and the Irish VOT transfer study a sample enumeration approach was used instead.

The sample enumeration was run as follows:

- The VOT was calculated for each car and PT observation by applying Equation (2.2) using the modelled costs for the chosen mode (so either car or PT) to the chosen destination
- The highway distance from the home to the chosen destination was also output
- Distance weighted average car and PT VOT values were then calculated
- Overall average VOTs were calculated using the observed car and PT mode shares.

In Table 5 we compare the estimated VOTs using the ERM ‘costs’ to the previous Irish SP VOT transfer values and the previous CAF values, together with the percentage changes.

Table 5: Transfer of UK VOT models to Ireland (VOTs in 2014 £/hr)

Purpose	ERM VOT models	Irish SP transfer values		Previous CAF values	
Commute – all modes	9.91	8.98	10%	11.79	-16%
Business – all modes				24.39	
Business – car	33.13	25.73	29%		
Other non-work – all modes	31.23	2.26	1282%	10.72	191%

For commute the RP VOT estimates from the ERM models are 10% higher than the Irish VOT transfer values but 16% lower than the previous CAF values, as such the estimates appear to be reasonable.

For business it was not possible to calculate a reliable PT VOT value due to the low number of PT observations, therefore the comparisons are made for car only. The RP estimates are 30% higher than the SP transfer values, the difference with the previous all mode CAF values is similar.

Other is the most problematic purpose. The cost variable was problematic in this model because there are significant numbers of people (e.g. the retired) for whom PT fares are all zero. A model was estimated with all retired persons excluded, this reduced the distance weighted VOT to 18.22 £/hr, a significant reduction but still a value that is much higher than both the Irish SP transfer values and the previous CAF values.

5.0 Summary and recommendations

This research has demonstrated that it is possible to estimate VOTs from RP data, specifically from mode-destination models estimated by combining RP travel survey data with network and land-use data.

UK meta-analysis demonstrates RP VOT estimates to be 22% higher on average than SP estimates. Two recent UK case studies have identified RP VOTs from mode-destination models that are either consistent or higher than the corresponding SP-based values given in TAG. However, in the London models it was not possible to estimate models that yielded VOT estimates for discretionary travel.

The Irish research work was prompted by a suspiciously low value of time for 'Other' non-work purposes when the Irish CAF values incorporated transferred VOTs from the UK TAG guidance. Using journey times and distance skims from the NTA's East Regional Model we then estimated VOTs in ALOGIT using revealed preference data from the Irish National Household Travel Survey from 2016 for both Car and PT trips.

For commute and business the results were consistent with the UK analysis, namely RP values that were in line with, or somewhat higher than, the corresponding SP values.

For other non-work we arrived at an estimate of 2014-GB-pounds 31.23 per hour from the RP models compared to 2.26 from the SP transfer. It is important to re-iterate that the PT fares in the ERM model are based on an average-type linear regression with distance for fares in many cases, hence not particularly accurate when paired with the travel survey data for trips. In the London models discretionary travel was also problematic, a key issue is that a significant amount of travel is made by travellers with zero fare on PT (mostly retired persons) and these observations make it difficult to estimate acceptable cost sensitivity parameters.

Ideally and perhaps in a future refinement of this work one would also include all inter-regional trips (especially to the metropolitan Dublin area) to ensure that the models are estimated using fully representative samples of trips. One could also perhaps work more directly with observed PT fares data instead of using the modelled fares regression but this is not straightforward.

We would like to thank Barry Colleary, Head of Modelling at the NTA, for commissioning the Irish research and for many helpful discussions and suggestions during a difficult period during Covid-19 restrictions.

Overall this work demonstrates that RP mode-destination models can be used to identify VOT estimates that are consistent with those obtained from SP VOT studies. The RP approach seems to work best for commute and business travel yielding values close to or somewhat higher than the SP estimates. For discretionary travel the RP approach is more problematic as it can be difficult to estimate acceptable cost sensitivity terms.

It is emphasised that while the RP mode-destination models discussed in this paper use observed RP choices they combine those choices with data from highway and PT assignment models that give *modelled* journey time information. If RP models were to be used for VOT estimation alone then it is recommended that alternative sources of network information be investigated and effort be given into ensuring that the costs represented for each individual match their actual costs as closely as possible. In mode-destination models developed for use in forecasting the trade-offs are different as a highly detailed segmentation will lead to infeasible run times.

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