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The valuation of delays in passenger rail using journey satisfaction data

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ABSTRACT

Stated preference surveys are typically used to derive lateness multipliers, defined as a trade-off between a minute of lateness and scheduled journey time. This study aims to use a novel in the context of lateness valuation dataset (i.e. responses from a survey on journey satisfaction) to apply it to the established methodologies. Travel satisfaction data from National Rail Passenger Survey in Great Britain is used to estimate the impacts of scheduled journey time and delay on passenger satisfaction. An ordered logit model with origin–destination pair fixed effects is estimated and lateness multipliers are subsequently derived. The estimated values are slightly larger than previously suggested, ranging from 4 to 9 for arrival delay (i.e. a minute of arrival delay is valued as an equivalent of 4–9 min of scheduled journey time) and 2 to 6 for departure delay. This study offers a degree of novelty in terms of the type of data used in the estimation process and highlights the potential of satisfaction surveys in economic valuation in transport.

1. Introduction

Transport researchers are interested in the impacts that different journey aspects, including scheduled journey times, fares, delays and comfort have on rail passengers. These are often evaluated using demand data (e.g. Wheat and Wardman 2017), stated preference (e.g. Batley and Ibáñez 2012) or satisfaction surveys (e.g. Monsuur et al. 2021). Regardless of the source of the data, there generally is a consensus in the literature that delays negatively impact public transport users, affecting both their satisfaction and travel behaviour. However, it has been suggested that the observed changes in demand in response to worsening performance (estimated in the market-level econometric analyses) are relatively limited as compared to the lateness valuation derived from individual-level discrete choice studies what can result from a lack of suitable alternatives (Batley et al., 2011).

Several studies attempted using Stated Preference (SP) data in the estimation of delay valuation, where the so-called lateness multipliers (also referred to as reliability multipliers by some authors) define the conversion rate of 1 min of average lateness to the equivalent of journey time and in this sense are defined as the trade-off between lateness (i.e. difference between actual and scheduled arrival time) and scheduled journey time (e.g. Börjesson and Eliasson 2011, Batley and Ibáñez 2012). In the British context, most studies supported the lateness multipliers of around 3 - i.e. 1 min of lateness being valued as the equivalent of 3 min of scheduled journey time (for review see Wardman and Batley 2014). The estimated valuations of late time can be used in the appraisal of journey time variability (Batley and Ibáñez, 2012).

This paper draws on earlier work using SP surveys to estimate lateness multipliers (e.g. Bates et al. 2001, Preston et al. 2009, Börjesson and Eliasson 2011, Wardman and Batley 2022 and particularly Batley and Ibáñez, 2012) whilst estimating the lateness

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multipliers using journey satisfaction data. At the same time, the methodology used in this study is similar to the large body of literature using data from surveys on life satisfaction (e.g. Layard et al. 2008, Dickerson et al. 2014). The major difference is the use of a survey on journey, not life, satisfaction and its cross-sectional nature. Building on the work by Monsuur et al. (2021), the National Rail Passenger Survey (a British survey of rail passengers) is used where passengers' satisfaction with experienced journeys is reported on a 5-point Likert scale. The passenger responses were matched to operational data to study the impact of the scheduled journey time and delays on passenger satisfaction. An ordered logit model of passenger satisfaction is used to estimate the utilities of both scheduled journey time and delay (at departure and arrival) for a pseudo-panel of frequent rail travellers. The estimated coefficients are subsequently used in the estimation of lateness multipliers.

Hence, the overall aim of this work is to use a novel in the context of lateness valuation dataset (i.e. responses from a survey on journey satisfaction) to apply it to the established methodologies to:

1. Explore the potential of journey satisfaction data in economic valuation in transport-related contexts and
2. Compare the lateness multipliers estimated from satisfaction data to the values obtained from the traditional methods (i.e. SP surveys).

This paper starts with a literature review, positioning the lateness multipliers within the British rail forecasting framework as well as a description of the data sources typically used in their estimation. This is followed by a description of the NRPS dataset used in this study and the modelling approach undertaken. Subsequently, the estimated models and lateness multipliers are presented, followed by a discussion and comparison with the values sourced from the literature. The final section summarises this work and discusses the potential for using satisfaction surveys in future research concerning economic valuation in transport.

2. Literature review

2.1. Lateness valuation framework

Ticket sales data is often used to estimate the effect that Generalised Journey Time (GJT) components have on rail demand (for a review see Wheat and Wardman 2017). Following Wheat and Wardman (2017), the rail demand function in Great Britain (GB) is specified as:

$$V = \mu GJT^{\lambda} F^{\gamma} GVA^{\delta} \quad (1)$$

where GJT is Generalised Journey Time, F is fare, GVA is income, λ, γ, δ are the respective elasticities and μ represents all the other factors impacting the demand. GJT in this formulation is a composite index specified as:

$$GJT = T + \alpha H + \beta I \quad (2)$$

where T is the station-to-station journey time, H is a service headway and I is the number of interchanges with α and β being the respective penalty multipliers converting both the number of interchanges and service headway into equivalent journey time.

Extending the demand specification presented in Eq. (1), Batley et al. (2011) used the following relationship between demand and average lateness at the destination, previously prescribed by the Passenger Demand Forecasting Handbook (PDFH) in Great Britain (Association of Train Operating Companies, 2005):

$$Y = [1 + \frac{w(L^{+}_{new} - L^{+}_{base})}{GJT_{base}}]^{\gamma} \quad (3)$$

where Y is the proportionate change in rail demand, L^{+}_{new} and L^{+}_{base} represent average lateness at the destination in the base and new scenarios, GJT_{base} is the Generalised Journey Time in the base scenario, λ is the elasticity of rail demand to GJT and w is the lateness (reliability) multiplier.

As noted by Wheat and Wardman (2017), PDFH is a set of guidelines and forecasting parameters that combine years of research into rail demand in Great Britain, providing a comprehensive and consistent framework for economic appraisal of railway schemes. Of note, as discussed by Wardman and Batley (2022), Eq. (3) represents the so-called 'indirect' approach to forecasting the impact of changes in railway performance. Since 2018 (PDFH v6), a recommendation was made to move to a 'direct' approach where a change in demand Y is estimated directly based on a change in average lateness and the late time elasticities (usually obtained from rail demand models, for review see Wardman and Batley (2014)).

The aforementioned lateness multiplier w defines the conversion rate of 1 min of lateness to the equivalent of journey time and in this sense is defined as the trade-off between lateness and scheduled journey time. It is typically estimated as the ratio of the utility of lateness to the utility of scheduled journey time. Wardman and Batley (2014) provide a review of estimates of lateness multipliers since 1984 with most of the initial values being around 3. Similar studies conducted throughout the years generally supported that figure but suggested values of up to 6.5 for airport journeys with Batley and Ibáñez (2012) estimating lateness multipliers for different demand segments based on journey purposes and lengths as shown in Table 1. As reported in Wardman and Batley (2014), in most cases, the estimated lateness multipliers range between 2-5 for business travellers and commuters and 2-7 for leisure travellers though values larger than 10 have also been reported throughout the literature (e.g. Wardman 2001, Börjesson and Eliasson 2011).

Table 1
Lateness multipliers for arrival delay estimated by Batley and Ibáñez (2012).

Journey purpose	Distance	
	Short	Long
Business	2.68	1.78
Commute	3.12	2.00
Other	5.19	1.77

2.2. Data sources used in the estimation of lateness multipliers

Stated Preference (SP) surveys are most often used in studies where lateness multipliers are estimated (e.g. Bates et al. 2001, Preston et al. 2009, Börjesson and Eliasson 2011, Li et al. 2016). In such cases, passengers are presented with alternative hypothetical travel options and make a choice regarding their preferred scenario. The differences in the options presented to the respondent are the ticket prices, scheduled journey times and performance (presented as average delay or distribution of delays). An example of such an approach is Batley and Ibáñez (2012) where one of the pairs of journey options shown to respondents was:

1. Option A where a 27-minute journey costs £2.40 with average lateness of 1 min at departure and 4.4 min at arrival.
2. Option B where a 23-minute journey costs £3.60 with average lateness of 4.4 min at departure and 8.8 min at arrival.

While the SP data can be subjected to biases, such as systematic bias (divergence between hypothetical and actual choices), justification bias (rationalising actual choices) or strategic bias (influencing policy) (for review see Wardman 1988), it has become a standard approach as it is often the only possible source of such data (Bates et al., 2001) as SP studies allow the analyst to design scenarios that may not be observable in the real world as well as explicitly control for the choice attributes (Tsoleridis et al., 2022). An alternative to stated preference data is revealed preference (RP) data where passengers' actual travel choices are investigated. While economists typically prefer data on actual choices, the RP data has its own limitations. It is more difficult to obtain, may be prone to reporting errors (especially in the case of traditional travel diaries) and is based on the assumptions of perfect information about the possible travel alternatives whereas, in fact, it is difficult to identify the choice sets and trade-offs faced by the participants (Wardman, 1988; Bates et al., 2001; Hess et al., 2007; Preston et al., 2009; Tsoleridis et al., 2022).

An alternative to SP and RP surveys can be sought in satisfaction surveys where passengers score their satisfaction with an actual travel experience *ex-post.* There is an abundance of literature looking at the impact of different journey aspects on passenger satisfaction (for reviews see De Vos et al. 2013, De Oña and De Oña 2015, Gao et al. 2018, Ye et al. 2022). Unlike SP or RP studies, passengers are not faced with multiple alternatives but score their satisfaction with a particular journey (though some studies analysed surveys referring to general satisfaction with public transport, i.e. Cats et al. 2015). Most studies cite travel time, performance, journey comfort and provision of information as key determinants of passenger satisfaction (e.g. Brons and Rietveld 2009, Carrel et al. 2016, Börjesson and Rubensson 2019, Lunke 2020, Monsuur et al. 2021). In the British rail context, Monsuur et al. (2021) used the National Rail Passenger Survey to estimate the impact of delays on passenger satisfaction, suggesting that passengers are very unlikely to remain satisfied with journeys delayed by over 30 min, also highlighting the importance of journey quality on travel satisfaction.

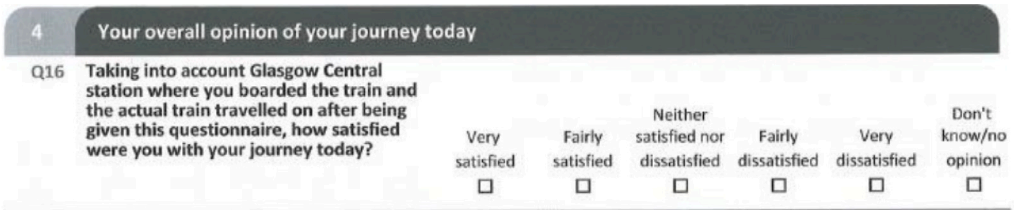
Whilst data on scheduled journey time and lateness may be available to supplement the reported satisfaction, it refers to incidental (i.e. for a specific journey), not mean or standard deviation of performance as is typically the case with SP surveys. Satisfaction data, typically from longitudinal household panels, have been used in economic valuation in labour (e.g. Layard et al. 2008), health (e.g. Ferrer-i-Carbonell and van Praag 2002) and environmental economics (e.g. Frey et al. 2009). However, similar approaches have not been as widely used in transport economics, possibly resulting from a lack of transport surveys with such detailed information or from household surveys lacking enough transport-related information. The most important exception is a study by Dickerson et al. (2014) looking at the relationship between commuting and life satisfaction.

3. Data and methodology

3.1. National rail passenger survey (NRPS) dataset

275,000 responses from 10 waves (between 2015 and 2020) of NRPS (Transport Focus, 2020a) in the UK were obtained directly from Transport Focus (for more details see Transport Focus 2020b). The dataset is a well-established data source in the UK and has been used in multiple studies, e.g. Monsuur et al. (2021) looking at the impact of delays on satisfaction, Stead et al. (2019) comparing satisfaction with open access and franchised operators or Lyons et al. (2016) looking at passengers' use of in-vehicle time.

The NRPS dataset is cross-sectional in nature. The survey is administered by intercepting passengers on trains or at stations in the course of making a journey. In each survey wave around 30,000 rail passengers across Britain are asked to report their satisfaction with multiple aspects of the completed journey with a typical completion rate of around 25%. The collected responses were subsequently matched with operational data using the Historic Service Performance platform (National Rail, 2020) to compute scheduled journey times and corresponding delay lengths for each of the passengers.


4 Your overall opinion of your journey today

Q16 Taking into account Glasgow Central station where you boarded the train and the actual train travelled on after being given this questionnaire, how satisfied were you with your journey today?

Very satisfied	Fairly satisfied	Neither satisfied nor dissatisfied	Fairly dissatisfied	Very dissatisfied	Don't know/no opinion
☐	☐	☐	☐	☐	☐

Fig. 1. Overall satisfaction question from NRPS.

The passengers scored overall satisfaction with their journey on a 5-point Likert scale, from 'very dissatisfied' to 'very satisfied' as shown in Fig. 1. Similarly, the survey includes questions related to (between others) satisfaction with the train, station, value for money and service frequency, representing the variety of journey aspects that may affect the overall journey satisfaction.

3.2. Pseudo-panel of frequent travellers from NRPS

With the NRPS dataset being cross-sectional in nature, an attempt was made to create a subset of the original dataset capturing frequent rail travellers. Pseudo-panel approaches have been widely used in the literature in the absence of true panel datasets (e.g. Dargay 2002, Rich et al. 2023). This pseudo-panel of frequent travellers was then used to investigate the impact of both scheduled journey time and delays on passenger satisfaction.

It is expected that while delays affect satisfaction of both frequent and infrequent travellers (i.e. as investigated in Monsuur et al. 2021), the scheduled journey time itself should not generally directly impact satisfaction with an individual journey. This is based on an assumption that travellers' decision to travel on a given service characterised by a timetabled scheduled journey time was one that maximised travellers' utility. Though, as suggested by Cats et al. (2015), longer journeys may be associated with lower overall satisfaction with public transport for commuters.

Let us illustrate this using an example of two journeys:

1. A long-distance 4-hour journey between London and Edinburgh
2. A short-distance 30-minute journey between London and Stevenage

The two examples presented above represent very different journeys. The first one is a much longer, leisure or business journey. The second one is a shorter, commuter-type journey. However, considering the cross-sectional nature of the dataset, it is not expected that the differences in the timetabled lengths of journey should have an impact on journey satisfaction of the two different types of travellers. Journey time is a source of disutility for passengers travelling on different origin–destination (OD) pairs, but assuming that both types of travellers are rational and aim to maximise their utility, the choice to travel from London to Edinburgh and from London to Stevenage is one that maximises their utility. Assuming that both services perform as timetabled, it would be expected that both types of travellers are satisfied with their journeys. Any differences in the satisfaction scoring may be due to the differences in other journey aspects (i.e. comfort) that may be correlated with journey length.

On the other hand, a frequent traveller, i.e. between London and Stevenage may be able to perceive changes in scheduled journey times (timetable). Such changes may, in turn, affect their journey satisfaction. Investigating this relationship is, however, only possible for panel (not cross-sectional) datasets where the same traveller scores their satisfaction with multiple different journeys on the same OD pairs across time. As mentioned previously, the NRPS dataset is cross-sectional in nature. However, an attempt was made to construct a pseudo-panel of frequent travellers to investigate whether and how changes in scheduled journey times and experienced lateness on the same OD pair, affected reports of journey satisfaction.

To align with this framework, a number of modifications was applied to the original NRPS dataset, based on the following journey characteristics:

1. Frequency of travel
   Out of the 46% of passengers responding to the question regarding the frequency of travel on a given route, 73% admitted to travelling at least every 2 months. It is assumed that delays may affect satisfaction of both frequent and infrequent travellers. However, it is only the frequent travellers whose satisfaction is assumed to be affected by potential changes in scheduled journey times on a given route.
2. Recorded delay length and delay perception
   Responses where a passenger reported late arrival but no delay was matched using the operational data (5.7%) were discarded, as were responses associated with delays of more than 30 min — so as to remove outliers and possibly erroneous responses as in some cases large differences between recorded and reported delays were found for these records. However, responses where no delay was reported and recorded were retained as the interest here is in both delayed and on-time journeys.
3. Number of responses for a given origin–destination (OD) pair
   OD pairs with more than 10 and 25 responses were selected. 792 OD pairs were identified with more than 10 responses (over 26,026 records) and 270 pairs with more than 25 responses (over 17,695 records). The response thresholds of 10 and 25 were selected based on judgment to find a compromise between the number of OD pairs and the number of responses per OD.

Table 2
OD pair distribution across journey type categories (based on model 4 with OD pairs with more than 25 responses).

Journey type	OD pairs	Distance category	Average scheduled journey time
Airport	11	–	28.5
High-speed	37	Long	89.5
Interurban	37	Long	60.3
Long commute	85	Short	47.7
Long distance	45	Long	106.9
Rural	11	–	45.6
Short commute	44	Short	34.5

In conclusion, between 14,000 and 40,000 responses are used in the estimation of the satisfaction models described in Section 3.3. This depends on the choice of OD pairs as well as control variables (i.e. the more control variables, the fewer the responses as some questions in the survey were subject to non-response).

3.3. Deriving the lateness multipliers

3.3.1. Ordered logit model of passenger satisfaction

As the dependent variable (satisfaction) can take one of the five outcome categories, which are in sequential order, an ordered logit model is used for estimating the latent continuous variable y^*. In this case, the probability of choosing a satisfaction category i is estimated for a given number of k categories, thus:

$$P(Y = i) = P(k_{i-1} < y^* \leq k_i) \tag{4}$$

where journey satisfaction is modelled as follows:

$$P(Y = i) = P(k_{i-1} < \beta_0 + \beta_1 SJT + \beta_2 L_D + \beta_3 L_A + \sum_{n=1}^{n} \beta_{Sat_n} Sat_n \leq k_i) \tag{5}$$

where:

SJT: scheduled journey time

L_A: length of delay at arrival (destination)

L_D: length of delay at departure (origin)

Sat_n: a dummy for a variable representing passenger's satisfaction with train and station (models 1-4) and also satisfaction with value for money and frequency (model 4). It takes the value of 1 if a passenger was 'very satisfied' or 'fairly satisfied' with a given journey aspect or 0 otherwise.

In models 2-4, OD pair fixed-effects are included by introducing a dummy variable representing each of the OD pairs included in the subsample. This allows treatment of the dataset, which is cross-sectional in nature, as a pseudo-panel of frequent rail travellers (as discussed in Section 3.2) to estimate the impacts of both changes in scheduled journey times and delays on passenger satisfaction.

3.3.2. Choice of control variables and demand segmentation

In terms of the choice of control variables, as noted previously, passengers' satisfaction with public transport is not only impacted by performance but also by other journey aspects, most notably journey comfort. Journey quality may be confounded with journey satisfaction, as better comfort may mean that travel time can be put to good use (Lyons et al., 2016; Wardman and Lyons, 2016).

63 different questions related to satisfaction with very specific journey aspects, as well as two more general questions, were asked throughout the 10 waves of the NRPS surveys waves. In each case, satisfaction was reported on a 5-point Likert scale with an option of no score if a passenger felt they did not know how to score this aspect or did not experience/use it (e.g. toilet facilities, catering, etc.). Many of these questions had a relatively low response rate or were not part of all the survey waves. Hence, the choice of the control variables was limited to the two general satisfaction questions — satisfaction with train and station as well as satisfaction related to timetable or performance, i.e. satisfaction with train frequency, punctuality, scheduled journey time and value for money. However, satisfaction with punctuality and scheduled journey time were discarded as these are, instead, represented in the model by the directly observed (experienced) values.

The analysis that follows employs segmentation to enable estimation of lateness multipliers for the different passenger and journey types. Only passengers travelling on certain ticket types were retained for further analysis, i.e. season tickets for commuters while passengers travelling using special tickets and passes were removed from the dataset. This is to ensure reasonable homogeneity of passengers represented in a given demand segment. The base model employs segmentation by three journey purposes — business, leisure and commute whilst the segmentation in the extended model aligns with that used in Batley and Ibáñez (2012) (i.e. by three journey purpose and two journey length categories) for better comparison of the estimated values. Therefore, all the responses were categorised based on the journey type classification provided in the dataset by Transport Focus and subsequently grouped as short and long distance as shown in Table 2 to align with Batley and Ibáñez (2012).

Tables 3 and 4 provide more detailed information about the distribution of responses across different segments as well as summary statistics for the variables used in the modelling.

Table 3
Distribution of responses across journey purpose and length categories (based on model 4a).

Distance	Journey purpose			Total
	Business	Commute	Leisure	
Short (%)	6.69	24.77	14.62	46.08
Long (%)	18.07	10.02	25.82	53.92
Total (%)	24.76	34.79	40.44	100

Table 4
Average values of the variables used in the modelling by segment (Overall refers to the dependent variable; Station, Train, Freq and VfM refer to the control variables where the satisfaction variable was converted from the original 5-point scale to a binary scale, thus the reported values show the proportion of satisfied respondents in relation to satisfaction with respectively station, train, train frequencies and value for money; L_A, L_D refer to recorded lateness at arrival and departure and SJT refers to scheduled journey time).

Segment	Overall	Station	Train	Freq	VfM	L_A	L_D	SJT
Short business	4.14	0.86	0.84	0.87	0.43	2.68	1.39	58.7
Short commute	3.82	0.80	0.72	0.75	0.20	2.16	1.31	35.3
Short leisure	4.36	0.90	0.88	0.90	0.62	1.95	1.14	51.1
Long business	4.15	0.84	0.84	0.88	0.44	3.68	1.31	103.5
Long commute	3.77	0.80	0.71	0.79	0.20	3.92	2.62	37.9
Long leisure	4.39	0.88	0.90	0.91	0.67	3.10	1.44	99.7

3.3.3. Lateness multipliers

Ordered logit model is conceptually more suitable for modelling ordinal data than linear regression (Dickerson et al., 2014, for review see Boes and Winkelmann (2006)), but its major limitation is the difficulty in interpreting the coefficients. However, as noted in Dickerson et al. (2014), the ratios of the coefficients in the ordered model can be used to evaluate the trade-offs between variables. In this case, lateness multipliers are estimated as a ratio of utility of departure and arrival delay β_2 and β_3 to the utility of scheduled journey length β_1 (i.e. following Batley and Ibáñez, 2012). The multipliers are calculated separately for the two types of delays, at departure (w_D) and arrival (w_A) following Batley and Ibáñez (2012) for the selected demand segments. In line with the literature (i.e. Bates et al. 2001, Preston et al. 2009, Batley and Ibáñez 2012), the lateness multipliers represent the value of delayed time with respect to the scheduled journey time:

$$w_D = \frac{\beta_2}{\beta 1} \text{ and } w_A = \frac{\beta_3}{\beta 1} \tag{6}$$

With reference to the satisfaction data used, the direct interpretation is that the lateness multipliers represent the equivalent increase in scheduled journey time needed to stimulate the same decrease in journey satisfaction as a minute of late running.

3.3.4. Summary

Two iterations of models were estimated using Stata 17 (StataCorpl, 2021) and are presented along two sets of estimated lateness multipliers. For each of the iterations, four alternative specifications of the models are presented. The base models (shown in Table 5) were estimated with a more limited segmentation whereas the extended models (presented in Table 7) followed the segmentation similar to that in Batley and Ibáñez (2012). In both cases, four sets of models are presented, a cross-sectional model and three models with OD fixed effects that differ with respect to the minimum number of responses per OD pair and control variables chosen (serving as sensitivity tests):

1. Ordered logit model without OD fixed effects;
2. Ordered logit model with OD fixed effects for a subset of OD pairs with at least 10 responses;
3. Ordered logit model with OD fixed effects, for a subset of OD pairs with at least 25 responses;
4. Ordered logit model with OD fixed effects, for a subset of OD pairs with at least 25 responses and additional control variables representing satisfaction with value for money (VfM_Sat) and service frequency ($Freq\_Sat$).

4. Results and discussion

4.1. Base models

The models of passenger satisfaction were estimated using an ordered logit model with estimated coefficients presented in Table 5. Model 1 is based on estimating the ordered logit without OD fixed effects. In this model, the delays at arrival and departure both have a statistically significant negative impact on satisfaction whilst the impact of scheduled journey time is less clear. As discussed previously, it is not expected that passengers on different OD pairs that travel longer are less satisfied with their journeys, as journey lengths naturally increase with distance. However, journey lengths may, indeed, be correlated with other journey aspects, i.e. delays or journey comfort. Hence, the need to control overall satisfaction for other journey aspects. This is represented by the positive impact that satisfaction with station and train is suggested to have on the overall satisfaction. However, it is worth noting the significant and negative coefficient on scheduled journey time under model 1 for commuters that may be potentially explained by commuters generally showing larger dissatisfaction with longer travel for work as indicated by Cats et al. (2015).

Nevertheless, it can be expected that respondents who travel on the same OD pair are sensitive to changes in scheduled journey times and it is further assumed that these impacts are similar for travellers on the same OD. With the introduction of OD fixed effects in models 2-4, the coefficients on scheduled journey time become significant and negative for all journey purposes, in line with expectations.

Using the estimated coefficients from Table 5, lateness multipliers for arrival and departure delay were calculated for models 2-4 as shown in Table 6. The estimated lateness multipliers at arrival are around 4.0-4.7 for business travellers, 7.4-8.9 for commuters and 4.6-5.6 for leisure travellers. The respective departure lateness multipliers are 5.6-6.0 for business travellers, 2.1-3.5 for commuters and 3.2-4.0 for leisure travellers. The three estimated models in Table 6 indicate that the model results are quite robust to reducing the sample size or inclusion of additional control variables (as the estimated lateness multipliers are of similar magnitude for models 2-4). The lateness multipliers are larger at departure for business travellers, slightly larger at arrival for leisure travellers and much larger at arrival for commuters. This would suggest that 1 min of delay is valued as being equivalent to around 4 min of scheduled journey time for delay at arrival and 6 min at departure for business travellers, 8 min at arrival and 3 at departure for commuters, and 5 min at arrival and 3 min at departure for leisure travellers.

It is, however, worth noting that lateness multipliers are ratios of two values — utility of scheduled journey time and delay and, hence, depend on their relative magnitudes. At the same time, the observed differences in the scheduled journey times are typically relatively small (i.e. average absolute difference in timetabled scheduled journey times was just above 4 min for the OD pairs in the subsample used in model 4). This highlights the limitation of satisfaction data as (unlike in SP experiments), the analyst has no control over the attributes of the presented choice sets (or scheduled journey times and experienced lateness in the case of satisfaction surveys). It is possible that the small differences may remain unperceived by some passengers (perhaps even by frequent travellers) or have a lower marginal valuation as compared to larger differences (Daly et al., 2014 discusses the possible non-linearities in relation to time losses and savings whilst Wardman and Batley, 2022 talks about the importance of time perception in relation to delays). If this is the case, the utility of scheduled journey time may be underestimated. In such cases, overcoming this limitation may be difficult as satisfaction data only allows scoring experiences *ex-post* and large changes in scheduled journey times are rarely observable.

4.2. Extended models

To enable closer comparisons with the work conducted by Batley and Ibáñez (2012) and provide sensitivity analysis to the estimation reported in Section 4.1, the ordered logit models were re-estimated using the extended version of journey type segmentation (presented in Table 4) with the results shown in Table 7. As in the case of the base model, model 1a is estimated without OD fixed effects that are subsequently included in models 2a-4a. Similarly to the base model, in model 1a, the scheduled journey time coefficient is negative and significant for commuters. With the inclusion of OD fixed effects in models 2-4, the scheduled journey time coefficient becomes negative and significant for all segments. At the same time, coefficients for arrival delay are negative and significant for all journey length and purpose combinations. However, in the case of departure delay, despite all of the coefficients being negative, they are not significant for short commute and leisure. This may be a result of the additional segmentation leading to fewer responses by demand segment.

The subsequently estimated lateness multipliers are shown in Table 8. Arrival delay multipliers are around 9 for short and 4 for long business journeys, 7 for short and 9 for long commute and 5–6 for leisure trips. The corresponding departure delay multipliers are 4–5 for business journeys, 1–3 for commute and 1–5 for leisure trips. There is less confidence in the departure delay multipliers as the estimated values tend to vary considerably between the estimated models.

4.3. Comparison of estimated lateness multipliers with Batley and Ibáñez (2012)

The lateness multipliers from the base model (with three demand segments) and extended model (with segmentation by journey purpose and length conforming to the segmentation adopted by Batley and Ibáñez 2012) were subsequently compared with the equivalent values estimated by Batley and Ibáñez (2012). These have been retrieved from Table 4b in Batley and Ibáñez (2012) for lateness multipliers at arrival whilst the lateness multipliers at departure were calculated from the estimated coefficients reported in Table 4a in Batley and Ibáñez (2012). These are presented in Fig. 2.

In the base models where no journey length categorisation was introduced, arrival lateness multipliers of respectively 4, 8 and 5 were estimated for business, commute and leisure travellers. With the introduction of journey length categorisation, the estimated multipliers for business travel were suggested to be larger for short journeys (around 10) and comparable to the base model for long journeys (around 4). For commuters and leisure, comparable lateness multipliers were estimated from the base and extended models — between 7 and 10 for commuters (slightly larger for the long journeys) and around 4–6 for leisure.

In the case of departure lateness multipliers, the values estimated from the base and extended models are very similar in all cases and do not seem to differ between short and long journeys. These are around 5–6 for business journeys, 2–3 for commute and 3–4 for leisure journeys.

The results are indicative of lateness valuation increasing with journey time for commuters, decreasing for business travellers and being constant for leisure travellers. Hence, business travellers are suggested to be less concerned with delays relative to scheduled

Table 5
Modelling results for the base models (coefficients for satisfaction with value for money and frequency have been omitted.

	1	t-stat	2	t-stat	3	t-stat	4	t-stat
Constant								
Commute	−0.078	−0.93	−0.225	−1.85	−0.186	−1.25	−0.117	−0.69
Leisure	−0.012	−0.14	−0.055	−0.48	−0.022	−0.16	−0.079	−0.49
Station_Sat								
Business	1.345***	20.32	1.350***	17.26	1.325***	15.10	1.137***	12.27
Commute	1.111***	27.59	1.183***	20.87	1.195***	16.40	0.980***	12.94
Leisure	1.401***	27.85	1.465***	21.53	1.413***	17.07	1.172***	13.56
Train_Sat								
Business	3.059***	45.77	3.066***	38.20	3.127***	34.03	2.866***	28.90
Commute	3.049***	72.16	2.998***	51.96	3.042***	41.61	2.770***	35.98
Leisure	3.438***	62.16	3.418***	46.02	3.401***	36.61	2.999***	30.14
L_ A (β_3)								
Business	−0.0505***	−8.82	−0.0567***	−8.89	−0.0521***	−7.68	−0.0537***	−7.53
Commute	−0.101***	−18.36	−0.1000***	−14.12	−0.114***	−13.05	−0.109***	−12.03
Leisure	−0.0593***	−12.30	−0.0583***	−9.74	−0.0570***	−8.45	−0.0576***	−8.20
L_D (β_2)								
Business	−0.0690***	−7.77	−0.0683***	−6.46	−0.0729***	−5.99	−0.0758***	−6.01
Commute	−0.0522***	−7.71	−0.0472***	−5.20	−0.0296**	−2.60	−0.0349**	−2.97
Leisure	−0.0404***	−6.30	−0.0421***	−5.02	−0.0354***	−3.54	−0.0402***	−3.84
SJT (β_1)								
Business	−0.0009*	−1.99	−0.0120***	−5.43	−0.0121***	−5.00	−0.0134***	−5.27
Commute	−0.0058***	−6.76	−0.0134***	−5.26	−0.0142***	−4.74	−0.0123***	−3.93
Leisure	0.0002	0.53	−0.0105***	−4.95	−0.0102***	−4.34	−0.0125***	−5.06
Threshold 1	−2.482***	−31.58	−2.890***	−4.55	−3.755***	−7.41	−3.501***	−6.47
Threshold 2	−0.919***	−12.66	−1.243*	−1.96	−2.112***	−4.19	−1.815***	−3.37
Threshold 3	0.772***	10.71	0.455	0.72	−0.410	−0.81	−0.047	−0.09
Threshold 4	4.396***	56.76	4.190***	6.60	3.293***	6.53	3.870***	7.17
N	40 363		25 457		17 316		16 632	
Log-likelihood	−36771		−22388		−15182		−13921	
r^2	0.234		0.246		0.231		0.267	
Fixed effects	No		Yes		Yes		Yes	
VfM and Freq	No		No		No		Yes	
Minimum N	1		10		25		25	

*** p<.01
** p<.05
* p<.1

Table 6
Reliability multipliers estimated from the base models.

Journey purpose	w_A			w_D		
	2	3	4	2	3	4
Business	4.74	4.31	3.99	5.72	6.02	5.64
Commute	7.43	8.02	8.86	3.51	2.08	2.83
Leisure	5.52	5.61	4.61	3.99	3.49	3.21

journey time for longer journeys — this may result from the productive use of in-vehicle times (as discussed in Lyons et al. (2016) and Wardman and Lyons (2016)) and/or correlation between journey length and quality. However, in the case of commuters, the importance of delays relative to journey time seems to increase slightly with journey length. This may be related to the general dissatisfaction with long commute as noted in Cats et al. (2015) or correlations with other journey aspects.

Nevertheless, the estimated lateness multipliers seem to be larger than the values estimated in Batley and Ibáñez (2012). This can be possibly related to the different nature of satisfaction data or a relatively less negative disutility of scheduled journey time estimated from the satisfaction models due to the aforementioned data limitations. In line with Batley and Ibáñez (2012), in almost all the cases, the arrival delay multiplier is larger than the departure delay equivalent, indicative of the final (destination) delay being typically a source of larger disutility.

5. Conclusions

This work adds a degree of novelty in using passenger satisfaction data instead of the typically employed SP survey data to estimate lateness multipliers, a conversion rate between the value of a minute of lateness to the equivalent length of scheduled journey time. This paper combined the previous work using life satisfaction surveys in economic valuation (i.e. Layard et al. 2008)

Table 7
Modelling results with extended segmentation, coefficients for satisfaction with value for money, frequency, station and train have been omitted (S, L refer to short and long journeys; B, C, L refer to business, commute and leisure).

	1a	t-stat	2a	t-stat	3a	t-stat	4a	t-stat
Constant								
SC	0.0358	0.24	−0.0185	−0.09	0.0268	0.1	0.00342	0.01
SL	0.286	1.76	0.322	1.4	0.464	1.65	0.240	0.75
LB	0.0544	0.32	0.141	0.53	0.226	0.72	0.0669	0.19
LC	0.0142	0.08	0.039	0.15	0.193	0.61	0.223	0.63
LL	−0.0295	−0.18	0.0242	0.09	0.183	0.59	−0.0142	−0.04
L_ A (β_3)								
SB	−0.0892***	−6.17	−0.109***	−6.5	−0.102***	−5.72	−0.106***	−5.64
SC	−0.101***	−15.36	−0.0978***	−11.12	−0.114***	−9.94	−0.106***	−8.83
SL	−0.0658***	−7.01	−0.0555***	−4.14	−0.0722***	−4.55	−0.0792***	−4.82
LB	−0.0429***	−6.51	−0.0473***	−6.52	−0.0422***	−5.45	−0.0463***	−5.66
LC	−0.109***	−9.45	−0.113***	−8.34	−0.123***	−8.07	−0.119***	−7.5
LL	−0.0576***	−9.77	−0.0623***	−8.93	−0.0574***	−7.4	−0.0545***	−6.71
L_D (β_2)								
SB	−0.0487*	−2.56	−0.0423	−1.82	−0.0578*	−2.19	−0.0627*	−2.28
SC	−0.0659***	−7.97	−0.0508***	−4.31	−0.0181	−1.12	−0.0295	−1.77
SL	−0.0560***	−4.78	−0.0633***	−3.77	−0.0252	−1.22	−0.0175	−0.8
LB	−0.0585***	−5.43	−0.0578***	−4.58	−0.0552***	−3.74	−0.0560***	−3.66
LC	−0.0261	−1.92	−0.0367*	−2.29	−0.0369*	−2.05	−0.0385*	−2.08
LL	−0.0332***	−4.12	−0.0345***	−3.4	−0.0362**	−3.01	−0.0454***	−3.64
SJT (β_1)								
SB	−0.00102	−0.7	−0.0115***	−3.44	−0.0109**	−2.81	−0.0115**	−2.84
SC	−0.00695***	−6.5	−0.0154***	−4.68	−0.0148***	−3.7	−0.0134**	−3.21
SL	−0.0007	−0.8	−0.0117***	−4.18	−0.0118***	−3.7	−0.0144***	−4.32
LB	0.000002	0	−0.0102***	−4.09	−0.0101***	−3.59	−0.0116***	−3.91
LC	−0.00334*	−2	−0.0114***	−3.49	−0.0127**	−3.28	−0.0121**	−2.97
LL	0.000119	0.31	−0.00960***	−3.99	−0.00906***	−3.35	−0.0115***	−4.02
Threshold 1	−2.421***	−16.91	−2.779***	−4.18	−3.350***	−5.9	−3.298***	−5.41
Threshold 2	−0.842***	−6.03	−1.107	−1.67	−1.672**	−2.96	−1.581**	−2.61
Threshold 3	0.865***	6.21	0.595	0.9	0.0369	0.07	0.184	0.3
Threshold 4	4.499***	31.53	4.348***	6.55	3.755***	6.63	4.114***	6.76
N	36 220		22 397		14 733		14 146	
Log-likelihood	−33007.8		−19694.8		−12928.6		−11862.8	
r^2	0.237		0.251		0.236		0.271	

*** p<.01
** p<.05
* p<.1

Table 8
Reliability multipliers estimated from the extended models.

Journey purpose	w_A			w_D		
	2a	3a	4a	2a	3a	4a
Short business	9.46	9.38	9.19	3.68	5.31	5.45
Long business	4.63	4.20	4.00	5.66	5.49	4.84
Short commute	6.33	7.72	7.91	3.29	1.22	2.21
Long commute	9.84	9.64	9.80	3.20	2.90	3.18
Short leisure	4.76	6.11	5.49	5.43	2.13	1.21
Long leisure	6.49	6.34	4.74	3.60	3.99	3.95

with work using passenger satisfaction surveys to study the impact of delays on passengers (i.e. Monsuur et al. 2021) and studies using SP surveys to estimate lateness multipliers (i.e. Batley and Ibáñez 2012). A subset of NRPS dataset provided by Transport Focus was used to create a pseudo-panel of frequent rail travellers to estimate an ordered logit model of passenger satisfaction with origin–destination pair fixed-effects to estimate the utilities of delay and scheduled journey time. Subsequently, their ratios were calculated to derive the lateness multipliers.

The estimated lateness multipliers are slightly larger than the ones typically estimated in the SP studies and some caution is needed while applying these values. To the best of our knowledge, it is the first study attempting to use journey satisfaction data in such an application. It does, however, highlight the potential of using such data in transport economics as the estimated coefficients and resulting multipliers are of expected signs and magnitudes.

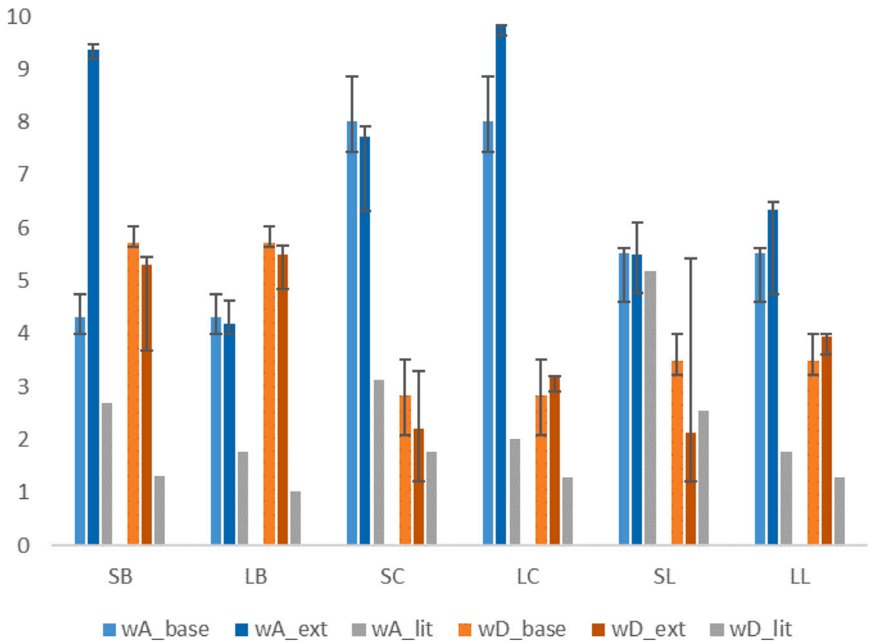


Fig. 2. Comparison of estimated lateness multipliers with Batley and Ibáñez (2012). (wA denotes lateness multipliers at arrival, wD — at departure; 'base' refers to the model with 3 demand segments, reported in Table 5; 'ext' refers to the models with additional demand segmentation reported in Table 7; 'lit' refers to the equivalent values estimated by Batley and Ibáñez (2012); for each of the estimated multipliers the error bars refer to minimum and maximum estimated value from models 2–4, while the median value is reported as the central value).

The results suggest that:

1. In most cases, delay at arrival is a source of larger disutility relative to delay at departure. This finding is in line with expectations and consistent with Batley and Ibáñez (2012). However, the opposite is suggested to be true for long business journeys, possibly due to the ability to more productively use the additional in-vehicle time related to onboard delays (for discussion on productive use of travel time see Lyons et al. (2016) and Wardman and Lyons (2016)).
2. Relative to scheduled journey time, 1 min of delay at arrival is valued as an equivalent of around 9 min of SJT for short business and long commute, 7 min for short commute, 5 min for leisure and 4 min for long business journeys. These values are typically larger than the estimates from SP studies with a minute of lateness valued up to 3 times more relative to scheduled journey time as compared with Batley and Ibáñez (2012). While the comparisons presented above are made in relation to the estimated values from Batley and Ibáñez (2012), it is noted that Wardman and Batley (2014) reported lateness multipliers between 2–5 for business travellers and commuters and 2–7 for leisure travellers with even larger values being reported in Wardman (2001) and Börjesson and Eliasson (2011).
3. The valuation of lateness at arrival respective to scheduled journey time is suggested to decrease with journey length for business travellers, increase for commuters and remain constant for leisure travellers. This is slightly different to the results obtained by Batley and Ibáñez (2012), suggesting that the valuation decreases with journey length.
4. Relative to scheduled journey time, 1 min of delay at departure is valued at around 5 min for business journeys and 2–4 for other travellers. These values are also larger than the estimates from SP studies with a minute of lateness valued up to 5 times more relative to scheduled journey time as compared to Batley and Ibáñez (2012).

The analysis presented as part of this paper highlights the potential of satisfaction data in economic valuation. As noted — it has been previously applied in economic valuation in health, labour and environmental economics. However, the application in transport has been very limited. Comparing satisfaction data to SP, RP or ticket sales data can offer some additional insights regarding the negative impacts (i.e. of delays) that are not reflected in hypothetical (i.e. SP) or actual (i.e. RP or ticket sales) choices. Hence, the different nature of the data can result in the lateness valuation being larger in the *ex-post* evaluations as compared to the hypothetical choices. As noted by Batley et al. (2011), the higher valuation of lateness at the individual level, but a much more limited impact of delays on demand may be explained by delays having a very negative impact on passenger satisfaction, but not necessarily leading to changes in demand. Even if worsening performance does not lead to changes in behaviour, it still has an impact on social welfare. The larger valuation of delay with respect to scheduled journey time, on the other hand, suggests that prioritising investment in improved reliability may have a larger than previously thought positive impacts on social welfare as compared to reductions in scheduled journey times. As noted by numerous articles, there is an increasing need to look at alternative ways of measuring social welfare (e.g. Fleurbaey 2009). Therefore, using journey or life satisfaction data and relating it to the supply of public transport as well as its performance can become a valuable addition to the standard economic approaches in transport appraisal.

It is believed that applying the methodology used in this study to similar journey satisfaction datasets would be useful in further exploring the potential of such data sources. In doing so, it is worth considering the following limitations of the NRPS dataset:

1. The dataset is cross-sectional in nature. The presented approach uses numerous assumptions to construct a pseudo-panel of frequent travellers. Using a true panel dataset would, therefore, be preferable. Moreover, the analysis of SP surveys typically focuses on the mean or standard deviation of performance (e.g. Batley and Ibáñez 2012). However, the recorded delay lengths and satisfaction scores in the NRPS survey refer to incidental journey experience.
2. The observed changes in scheduled journey time as well as delay lengths are naturally beyond the researchers' control. The scheduled journey times are defined by the differences that depend on the timetable whilst delay incidence and length depend on whether delays occur when surveys are conducted. With most changes in scheduled journey time being relatively small, it is possible that utility of scheduled journey time is less negative than it would be for larger changes. This could be the reason for the estimated multipliers being larger than the ones typically estimated in the literature. Therefore, conducting similar surveys may be useful for OD pairs that present interesting case studies, allowing for studying the impact of smaller and larger differences in journey times. Ensuring representation of delays of differing lengths is more difficult, as ideally, the surveys would need to be conducted over a long time period of time to increase the chances of observing shorter and longer delays.
3. The NRPS dataset may also be prone to data errors related to travel records as in some cases passenger reports of delay experiences were significantly different from the recorded performance, especially for the longer delays. This may be due to possible differences between the journeys the travellers planned to make, actual, reported journeys and interchanges.

While for the future studies, it is recommended that the aforementioned limitations are considered, the approach presented in this chapter led to the estimation of utility of scheduled journey time and lateness that were both of expected direction (i.e. negative) and magnitude (i.e. delay coefficient being more negative than that of scheduled journey time) what shows the potential that satisfaction data has in economic valuation.

The approach used here was based on demand segmentation aligning with the work by Batley and Ibáñez (2012). However, some alternative segmentations could be applied based on sociodemographic characteristics. Moreover, a cluster analysis could be applied to identify the different types of passengers from the dataset rather than using the pre-defined categorisation of respondents.

It is recommended that accurate data on journey history is collected from the satisfaction surveys to allow detailed investigation of the journey that the traveller was planning to make and their actual experience to reduce scope for errors. Moreover, including more questions related to income and fares in the questionnaires could allow the estimation of more sophisticated metrics. In the case of NRPS, this could be based on the investigation of the relationship between income, fare, scheduled journey time, headway, performance, journey quality and satisfaction with value for money, possibly even allowing calculation of the value of time.

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CRediT authorship contribution statement

Kacper Rossa: Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Andrew S.J. Smith:** Funding acquisition, Supervision. **Richard P. Batley:** Conceptualization, Funding acquisition, Supervision. **Phillip Hudson:** Funding acquisition, Supervision.

Availability of data and materials

The raw data from NRPS was obtained directly from Transport Focus and subsequently matched to operational data from HSP obtained from National Rail.

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