



A framework for joint modelling of activity choice, duration, and productivity while travelling



Jacek Pawlak^{a,b,*}, John W. Polak^{a,b}, Aruna Sivakumar^a

^a Centre for Transport Studies, Department of Civil and Environmental Engineering, Imperial College London, London SW7 2AZ, United Kingdom

^b Urban Systems Laboratory, Imperial College London, London SW7 2AZ, United Kingdom

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ABSTRACT

Recent developments in mobile information and communication technologies (ICT), vehicle automation, and the associated debates on the implications for the operation of transport systems and for the appraisal of investment has heightened the importance of understanding how people spend travel time and how productive they are while travelling. To date, however, no approach has been proposed that incorporates the joint modelling of in-travel activity type, activity duration and productivity behaviour.

To address this critical gap, we draw on a recently developed PPS framework (Pawlak et al., 2015) to develop a new joint model of activity type choice, duration and productivity. In our framework, we use copulas to provide a flexible link between a discrete choice model of activity type choice, a hazard-based model for activity duration, and a log-linear model of productivity. Our model is readily amenable to estimation, which we demonstrate using data from the 2008 UK Study of Productive Use of Rail Travel-time. We hence show how journey-, respondent-, attitude-, and ICT-related factors are related to expected in-travel time allocation to work and non-work activities, and the associated productivity.

To the best of our knowledge, this is the first framework that both captures the effects of different factors on activity choice, duration and productivity, and models links between these aspects of behaviour. Furthermore, the convenient interpretation of the parameters in the form of semi-elasticities enables the comparison of effects associated with the presence of on-board facilities (e.g., workspace, connectivity) or equipment use, facilitating use of the model outputs in applied contexts.

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1. Introduction

The time that people spend travelling is a pivotal focus of attention in travel behaviour research. Dimension such as the amount of time that people spend travelling, the influence of travel time on travel-related choice behaviour and the role of travel time savings in policy appraisal and evaluation have all been extensively researched. Until recently, however, the question of what people actually do during episodes of travel – the use they make of the time they spend travelling – has received comparatively little attention. This is a rather curious omission, since except in those rare situations where the

* Corresponding author.

E-mail addresses: jacek.pawlak@imperial.ac.uk (J. Pawlak), j.polak@imperial.ac.uk (J.W. Polak), a.sivakumar@imperial.ac.uk (A. Sivakumar).

performance of the travel task itself is completely all-consuming, leaving little or no physical or cognitive resource available for other tasks, the time we spend travelling is in principle as available, useful and potentially productive as any other type of time.

In recent years however, a number of factors have combined to heighten research interest in the subject of in-travel time use. The first factor is the accumulation of a growing body of theoretical and empirical evidence demonstrating that the use of in-travel time is extensive, multi-faceted and important. Empirical studies conducted in recent years, using both quantitative and qualitative approaches, have consistently demonstrated that travel time can be populated with a range of different economic and social activities conducted individually and in groups (Axtell et al., 2008; Frei et al., 2015; Gamberini et al., 2012; Holley et al., 2008; Keseru and Macharis, 2017; Lyons et al., 2016; Lyons and Urry, 2005; Susilo et al., 2012). This work can be seen as part of a wider discourse concerning the concept of multitasking, i.e. 'simultaneous conduct of two or more activities during a given time period.' (Kenyon and Lyons, 2007, p. 162). The concept of multi-tasking, while recognised in sociology for quite some time (Gershuny and Sullivan, 1998; Harvey, 1993) has only recently seen a more systematic treatment in travel behaviour and time allocation modelling studies (Circella et al., 2012; Pawlak et al., 2016; Pawlak and Polak, 2010). The emerging consensus is, therefore, that the presence of multiple activities, including those conducted while travelling, cannot be neglected, and this consensus is now captured in a number of leading national time use surveys, e.g. in Canada and the UK (Gershuny and Sullivan, 2016; Statistics Canada, 2011).

A second, and closely related factor has been the continuing evolution of Information and Communication Technologies (ICT), especially mobile services (Lyons and Urry, 2005; Wardman and Lyons, 2015). In particular, new ICT mobile services provide a means through which travel episodes, conventionally seen as 'wasted', can be transformed into more usable, enjoyable, and often personalised experiences (Watts and Urry, 2008). Whilst the field of ICT and travel behaviour relationships has traditionally focused on substitution and complementarity between physical travel and virtual participation in so-called tele-activities (Andreev et al., 2010; Salomon, 1986), developments in mobile ICT services have encouraged research on the modification of travel, such as travel time use and the associated productivity. Wardman and Lyons have asserted that 'past revolutions in transport that have made longer journeys possible are now joined by a digital revolution that is reducing the disutility of travel time' (Wardman and Lyons, 2015, p. 507). Investment in communications infrastructure to enable mobile connectivity has emerged as a commercially potent topic in a wide range of contexts, including e.g., provision of high quality in-flight connectivity; this market alone is estimated to amount to between \$2.1 and \$4.62 billion by the mid-2020s (Euroconsult, 2014; SMR, 2016).

The third factor driving increased interest in in-travel time use is its implications for the appraisal of transport investment. In particular, if travel time is more useful than was previously thought, how should investments in *reducing* travel time be appraised compared to those that *improve the capacity of* travel time to be used constructively? Any departure from the typically prevailing assumption that travel time is 'wasted' might have major implications for transport modelling and investment appraisal practice. Despite the fact that this issue was recognised by Hensher as far back as in 1970s, who suggested a systematic treatment of time use in the evaluation of employer and employee benefits (Hensher, 1977), there remains no consensus regarding the extent to which such effects should be accommodated in appraisal methodologies (Wardman and Lyons, 2015). This has been in spite of the fact that this issue was recognised as far back as in 1970s by Hensher who suggested a systematic treatment of time use in evaluation of employer and employee benefits. The so-called Hensher's equation has been subsequently formalised and derived from first principles (Batley, 2015; Fowkes et al., 1986), although its application remains fairly limited, especially with respect to the understanding of the role of various factors, including ICT. Indeed, the continuing rapid evolution in ICT capabilities magnifies the challenge faced by policy-makers and practitioners in seeking to adapt existing approaches when there is no clear and stable theoretical framework or practical roadmap for change. It is hence not atypical to observe a resort to status quo assumptions or ad-hoc approaches in light of the lack definitive evidence or a means of systematic treatment (cf. Batley et al., 2012; Mackie et al., 2003).

The final reason for the re-ignited debate on the nature of in-travel time use is the continuing development in vehicle automation technologies, and hence the prospect of fully driverless and connected vehicles. One of the primary benefits asserted for such technologies is the re-purposing of the previously, seemingly 'wasted' driving time, for more enjoyable and productive activities (see Milakis et al., 2017 for a review of relevant studies). For example, Thomopoulos and Givoni (2015) quote a US Department of Transport analysis putting the productivity gains at \$507 billion/year in the United States alone. This has all been in spite of growing evidence that there are complex trade-offs between potential improvements in network capacity and ensuring an enjoyable and productive on-board experience (Le Vine et al., 2015). Nevertheless, when, or if, the full automation of vehicles becomes possible and widely adopted, it is very likely to lead to step-changes in how transport systems function. Hence a framework that can suitably model in-travel time use and productivity is essential to understand adoption and use patterns of connected and autonomous vehicles (CAV) as well as their impacts on transport systems.

1.1. Objectives and structure of the paper

Motivated by the context outlined above, in this paper we develop a unified and comprehensive empirical framework enabling the investigation of factors driving in-travel time use and experience, including productivity. We demonstrate how this empirical framework is based on the microeconomic theoretic framework recently presented by the authors (Pawlak et al., 2015), referred to below as the PPS framework. The empirical framework is operationalised by using a copula formulation to

link a discrete choice model of activity type choice with a hazard-based model of activity duration, and a log-linear model of productivity (although without any loss of generality for any type of performance indicator). We apply the model in the context of modelling in-travel time use and productivity by business rail passengers in the UK. To the best of our knowledge, this is the first attempt at such a joint formulation in the context of travel time, and provides a powerful and flexible way of exploring factors shaping travel time, potentially applicable to any type of activity or mode of transport.

This paper is structured in the following way. Section 2 presents a brief review of the existing literature covering both conceptual and modelling approaches. In Section 3 we describe our approach, both in terms of its derivation from the PPS microeconomic framework and its econometric operationalisation. Section 4 presents empirical data from 2008 UK Study of the Productive Use of Rail Travel-time (SPURT) (DfT, 2009), which are used to estimate the model. The associated findings are discussed in Section 5, while conclusions are drawn in Section 6.

2. Previous studies

The past two decades have seen the emergence of a substantial body of empirical research on the topic of travel time use. The existing work ranges from conceptual and small scale qualitative studies (Bull, 2004; Churchill and Wakeford, 2002; Hara et al., 2001; Kenyon and Lyons, 2007; Laurier, 2004, 2002; Line et al., 2011; O'Hara et al., 2002; Oulasvirta and Sumari, 2007; Perry et al., 2001; Price and Matthews, 2013; Puuronen and Savolainen, 1997; Ünal et al., 2013; Watts, 2008; Watts and Urry, 2008; Weight, 2008), to large quantitative studies (Dong et al., 2015; Ettema et al., 2012, 2010; Gamberini et al., 2012; Holley et al., 2008; Lyons et al., 2016; Rhee et al., 2013; Susilo et al., 2012; Van der Waerden et al., 2009; Wener and Evans, 2011). Recent work also addresses the impacts on value of travel time and the associated implications for the appraisal of investments (Hultkrantz, 2013; SDG, 2016; Verschuren and Ettema, 2007), and even safety, given the effects of use of mobile devices while driving (Hislop, 2012; Lim and Chi, 2013; White et al., 2010). Below, however, we present only those studies that we identify as key contributions to the development of a modelling toolkit for in-travel time use and productivity. Otherwise, the recent review by Keseru and Macharis (2017) provides a succinct summary of the empirical findings to date.

From the conceptual point of view, Lyons and Urry (2005) hypothesised how attributes of transport modes may translate into travel time productivity distributions, and thus attractiveness of participation in in-travel activities. This has followed from the remark of Mokhtarian and Salomon (2001) who noted that utility derived from in-travel activities was one of the three components of the overall utility associated with travel, along with utility derived from destination activities and from the act of travelling itself. The more recent contribution of Circella et al. (2012) discussed travel time use in relation to the wider concept of multitasking, including possible sources of more or less efficient undertaking of activities while travelling.

One of the earliest systematic approaches to the issue of travel time use dates back to the 1970s, in the form of David Hensher's framework for the valuation of travel time savings of airline business passengers (Hensher, 1977). Although not directly aiming to model the effects of various factors on activity choice, duration or productivity, the so-called Hensher's equation (HE) has become a cornerstone in the valuation of travel time savings taking into account travel time use. While HE was formalised algebraically in the 1980s by Fowkes et al. (1986), it has been formally derived from microeconomic first principles only relatively recently (Batley, 2015). Wardman et al. (2013), however, have showed that despite its appealing nature, it is relatively difficult to HE in real world applications, especially in the absence of a detailed framework for modelling in-travel activity choice or productivity.

In another study, Banerjee and Kanafani (2008) presented a set of microeconomic models for travel time use, developed by extending time allocation frameworks originally proposed by Jara-Díaz and Guevara (2003). The authors were motivated by emerging efforts to deploy wireless connectivity on trains, and the possible impact of this on travel time savings valuation and on mode choice decisions. Their contribution was perhaps the first to demonstrate how incorporation of travel time connectivity or work-related productivity (termed 'efficiency score') into a time allocation framework leads to their presence in the resulting utility of a mode of travel and, thus, possible effect on the valuation of travel time savings. Their final framework was an allocation model, however, which did not explicitly treat activity choice decisions or the timing of particular activity episodes. As a result, it does not permit more detailed characterisation of travel time use, such as the number of activity spells or their order.

One of the more comprehensive, although underexposed treatment of in-travel time activities was offered by Hu (2009). Focused on the impacts of mobile commerce, Hu drew upon the microeconomic time allocation and goods-leisure paradigms (Becker, 1965; Jara-Díaz, 2007; Train and McFadden, 1978) to develop a utility-maximisation framework showing how travel time use could affect the utility of travel, and more generally, activity-travel patterns. Hu operationalised her model by means of a discrete choice theory that was estimated using stated preference data, although she did not specifically address in-travel time allocation and the productivity implications resulting from the on-board use of ICT.

Motivated by the works of Hu (2009), Pawlak and Polak (2010) sought to extend the standard time allocation theory to account for the possibility of multitasking. They proposed a tensor (multidimensional extension of 2-dimensional matrix) formulation in which dimensions represented layers of multitasking (secondary, tertiary, etc. activities) and row numbers particular activity types. In this representation, the value of a particular element of the tensor denotes the time allocated to a set of activity types undertaken simultaneously, as defined by the intersection of the respective row numbers in different dimensions. The authors also demonstrated that such a formulation requires a combinatorial weighting to ensure consistency and avoid double counting. Hence the weighted sum across all elements of the tensor needs to amount to the total time

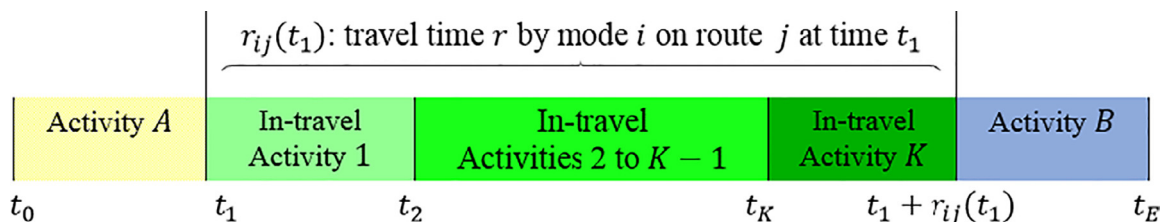


Fig. 1. Conceptual representation of time use during travel.

available to an individual. In a recent paper [Pawlak et al. \(2016\)](#) employed the 2-dimensional version of this constraint to extend the time allocation model proposed by [Jara-Díaz \(2007\)](#). As part of their contribution they derived expressions for optimal time allocation to activities, both primary and secondary, and operationalised the framework using a set of log-linear regressions with correlated error terms. Similar to most time allocation models, however, their framework looked at total time allocated rather than at a more detailed time use profile.

In a different contribution, [Zhang and Timmermans \(2010\)](#) presented a model of in-travel activity type choice using a skewed-logit (scobit) formulation. In their approach, an individual was assumed to evaluate whether or not to switch to a different activity type at fixed intervals. As a consequence, the actual durations would only be by-products of the model, and potentially biased, given the possibility that an activity finished within the interval. Hence they called for efforts to develop more elaborate simultaneous treatments of activity choice and duration, including looking at the role of ICT in travel time use decisions.

The study by [Rasouli and Timmermans \(2014\)](#), meanwhile, sought to incorporate utility from in-travel activities into utility of travel, assumed to comprise of the pure disutility of travel, and the utility of non-travel experiences. In their study, they asked respondents to rate their previous episodes of travel on a scale from 1 to 10 which they used as direct utility values. They subsequently regressed those values on pre-, post-, and in-travel activity types, controlling for sociodemographic attributes, transport modes, time of day, and presence of companions. While they demonstrated links between in-travel activities and the overall experience, as measured by the directly-reported utility, they did not explore factors affecting time allocation itself, nor tried to quantify productivity-related impacts.

Finally, a recent contribution from [Frei et al. \(2015\)](#) presented a joint model of service value, modelled as a latent variable, and travel time activity participation. While the authors presented parameters driving participation in a particular type of activity (work, active leisure, passive leisure), they did not seek to investigate the duration or productivity aspects.

Overall, while recent decades have seen developments in models of travel time use, to date, no unified and joint approach for activity choice, duration and productivity has been offered. We seek to address this gap by presenting a novel framework in the next section.

3. The modelling framework

The present approach draws upon the authors' earlier microeconomic framework for the joint choice of activities, mode and route, ICT use, and trip timing ([Pawlak et al., 2015](#)). The PPS framework assumes an individual who operates in a reference period delimited by the start and end times, t_0 and t_E respectively ([Fig. 1](#)). This period consists of pre- and post-travel activities *A* and *B* respectively, with a travel episode in-between with the duration r entailing the use of travel mode i , route of travel j , and the departure time t_1 . This frame of reference is conceptually similar to that of the 'activity envelope' proposed by [Rasouli and Timmermans \(2014a, p. 70\)](#) which emphasises the need to place the travel episode within a wider pre- and post-journey activity context. The reference period can be used as a building block for more complex travel situations, such as multi-leg journeys or trip chains and therefore does not limit generality of the discussion.

While travelling, an individual can engage in K spells of different in-travel activity types chosen from set \mathbf{L} , some of which may be recurrent while others may remain unchosen. For example, an individual can start by working, followed by a spell of leisure, and subsequently another spell of work, resulting in three spells and two activity types. The specific pattern of activity choices, and therefore also durations, will be driven by the relative utilities associated with undertaking specific activity types at particular times. These utilities will in turn depend on various factors such as journey context, respondent attributes, available facilities and devices (including ICT) for which various empirical evidence exists as highlighted in [Section 2](#).

3.1. Microeconomic formalisation

[Pawlak et al. \(2015\)](#) formulated the situation depicted in [Fig. 1](#) as a utility maximisation problem utilising the concepts of instantaneous utility, u , and intensity, z , of activities, thus describing the utility derived from participating in an activity with a specific intensity at a particular moment ([Ashiru et al., 2003](#); [Ettema et al., 2007](#); [Ettema and Timmermans, 2003](#); [Hu, 2009](#); [Polak and Jones, 1994](#)). They specifically assumed an individual seeking to maximise their overall utility U during the reference t_0 to t_E by choosing their level of goods consumption x , pre-, post- and in-travel activity types (A , B , and T_1 - T_K

respectively), departure time t_1 , activity timings t_2 to t_K , use of ICT ψ , as well as mode i and route j of travel (Eq. (1)). The utility to be maximised is described in terms of a set of integrals which express the total utility derived from an activity of a particular duration using the concepts of instantaneous utility and intensity.

In this formulation, utility is derived from two different sources: intensity and consumption. The dual source of the utility results from the assumption of the additive separability of utility and intensity, which permits tractability. While convenient from the point of view of tractability and reduction in dimensionality of the optimisation problem, this assumption is potentially debatable due to its implicit assumption of virtually perfect substitutability between consumption and all other factors. PPS interpreted this as a first-order approximation to the true utility function, claiming it a reasonable assumption in light of the short time scale and prior use, e.g. in models of time allocation and modal choice (Bates, 1987; Jara-Díaz, 2003, 2007).

$$\begin{aligned} \max_{x, t_1, t_2, \dots, t_K, A, B, T_1, \dots, T_K, i, j, \psi} \quad & U = \int_{t_0}^{t_1} (u_{zA}(z_A) + bx)dt + \int_{t_1}^{t_2} (u_{zT1}(z_{T1ij}) + bx)dt + \dots + \\ & + \int_{t_K}^{t_1+r_{ij}(t_1)} (u_{zTK}(z_{TKij}) + bx)dt + \int_{t_1}^{t_1+r_{ij}(t_1)} (u_{zTi}(z_{Tij}))dt + \\ & + \int_{t_1+r_{ij}(t_1)}^{t_E} (u_{zB}(z_B) + bx)dt \end{aligned} \tag{1}$$

subject to

$$\begin{aligned} w_A \int_{t_0}^{t_1} z_A dt + w_{T1} \int_{t_1}^{t_2} z_{T1ij} dt + \dots + w_{TK} \int_{t_K}^{t_1+r_{ij}(t_1)} z_{TKij} dt + \\ + w_B \int_{t_1+r_{ij}(t_1)}^{t_E} z_B dt + I = \int_{t_0}^{t_1} x dt + \int_{t_1}^{t_2} x dt + \dots + \\ \int_{t_K}^{t_1+r_{ij}(t_1)} x dt + \int_{t_1+r_{ij}(t_1)}^{t_E} x dt + c_\psi + c_{ij} \end{aligned} \tag{2}$$

The first utility component, denoted by u_z , depends on intensity z , which in turn captures the impact of activity timing t , various external contextual factors, e.g. journey purpose, presence of a companion, on-board facilities, socioeconomic attributes (collectively denoted as θ), as well as the availability and quality of ICT ψ . Furthermore, the intensity will depend on the mode i and route j to express the role of modal and route characteristics on the quality of in-travel activities, e.g. cycling on a busy urban street versus sitting on an intercontinental plane. Overall, the intensity is a function of all these factors, i.e. $z_{ij}(t, \psi, \theta)$ although this notation is simplified throughout the paper for the ease of comprehension. In Pawlak et al.'s framework the intensity term z is further assumed to serve as a proxy measure of productivity in the case of work-related activity types (denoted as \mathbf{W}). This translates into the utility associated with participating in work-related activity being dependent on the productivity experienced, which in turn can be affected by the terms t , ψ or θ . See Pawlak et al. (2015) for a more detailed discussion.

The second utility component, bx , captures the role of the general consumption level x , and the associated marginal utility of consumption b . In this way, the framework incorporates the role that consumption goods can potentially have on the quality of activity participation (Winston, 1982). Finally, the term $u_{Ti}(z_{Tij})$ in Eq. (1) captures the (dis)utility derived from the act of travelling itself via a particular mode and with a particular intensity (Mokhtarian and Salomon, 2001).

In order to prevent the individual from arbitrarily increasing the utility by raising their consumption level, PPS proposed a budget constraint (Eq. (2)). The left hand-side of this constraint describes the income available to an individual from participation in activities with specific intensity, z , and salaried at wage level w , or from other sources I . Note that this is a general expression: for non-work activity types (\mathbf{LW}) wage can be constrained to zero whilst for work-related activities, \mathbf{W} , it is positive and z expresses the productivity. The right hand-side is expenditure on consumption x , as well as on ICT use and transport c_ψ and c_{ij} respectively. All quantities are expressed in real terms, in relation to the consumption price level.

In contrast to most time allocation models, the PPS framework does not include an explicit time constraint. In fact, it is the presence of fixed temporal boundaries t_0 and t_E together with the integral formulation which serve as an implicit time constraint. Hence the model effectively looks at what Guevara (2017, p. 989) calls ‘the relevant chain of activities’. Within those boundaries, PPS derived an expression for the subjective value of travel time savings (Jara-Díaz, 2007). They observed that the value attached by an individual to such reduction is derived from longer participation in post-journey activity (assuming no change in the departure time) reduced by any utility associated with in-travel activities (and their impact on overall consumption utility) as well as the act of travelling itself.

Using this framework, PPS derived a decision rule followed by an individual when allocating their in-travel time between activities, given the context captured by the terms i, j, t, ψ or θ . Specifically, to ensure that the utility is maximised over the whole reference period, the rule in-travel time allocation is at time t to be engaged in an activity type T_i which delivers the

highest indirect utility V_{T_i} at that moment (Eq. (3)):

$$\begin{aligned} \max_{T_i} V_{T_i} |_{t,i,j,\psi,\theta} &= u_{T_i}(z_{T_i}) + bw_{T_i} z_{T_i} \\ \forall t, t_1 \leq t \leq t_1 + r_{ij}(t_1) \\ T_i &\in \mathbf{L} \end{aligned} \tag{3}$$

This utility is derived directly from the intensity, which is the first RHS term, and from the contribution to consumption, which is the second RHS term. Consequently, when looking at how to allocate their in-travel time, the individual continuously evaluates which activity type it is best to engage in and switches as necessary so as to maintain the highest V_{T_v} ¹. This in, turn, implicitly determines the duration of activities and their order.

In addition, it is assumed that intensity, z , serves as a proxy for instantaneous productivity for work-related activity types, i.e. those belonging to set \mathbf{W} ; thus enabling the mean in-travel relative productivity, ζ_{ij} , experienced by an individual on a particular transport mode i and route j to be defined (Eq. (4)):

$$\zeta_{ij} = \frac{\sum_{T_k \in \mathbf{W}} \int_{t_k}^{t_{k+1}} z_{T_k ij}(t, \psi, \theta) dt}{\sum_{T_k \in \mathbf{W}} (t_{k+1} - t_k)} \tag{4}$$

Eq. (4) describes the productivity as the total work-related output from all spells of in-travel work-related activities ($T_k \in \mathbf{W}$) divided by the total duration of those activities. The dependence of z on i, j, t, ψ or θ provides a theoretical link between the in-travel productivity and a variety of external factors that have been discussed conceptually and empirically in the literature (see [Keseru and Macharis, 2017](#), for a recent review).

Overall, Eqs. (3) and (4) are constructs that link the framework to an econometric formulation amenable to estimation.

3.2. Econometric formalisation

In the present context, the framework above can be used to develop models for the following three aspects of travel time use:

- the choice of an activity type for each spell;
- the duration of each activity spell;
- the in-travel productivity.

While the components above can be formulated as separate models, we seek to model them jointly. This follows from the theory above, which postulates the existence of links between these components. To account for this possibility, we propose a joint formulation using a copula approach, which is described in [Section 3.2.4](#).

3.2.1. Activity choice component

The inherently discrete nature of activity type makes discrete choice modelling a natural econometric formulation for the activity choice component, and, accordingly, this approach has been widely used in practice ([Bhat, 1997](#)). In the present context, we model the discrete alternatives as combinations of ‘entry’ (commencing) and ‘exit’ (subsequent) activity types, T_v and $T_{v'}$ respectively. In this manner, we account for the possibility that both the current and the subsequent activity types may affect the duration of the present activity. This stems from the fact that should the subsequent activity type become more attractive sooner, the current activity will naturally be shortened (this will be discussed more in the modelling of the duration component).

More formally, consider an activity spell of type T_v lasting from t_k until t_{k+1} when switching to type $T_{v'}$ takes place (and $T_v \neq T_{v'}$, i.e. the switching is to a different activity type) and define the associated indirect utility $V_{T_v \rightarrow T_{v'}}$, following from Eq. (3), as (Eq. (5)):

$$V_{T_v \rightarrow T_{v'}} = u_{T_v}(z_{T_v}(t_k)) + bw_{T_v} z_{T_v}(t_k) + u_{T_{v'}}(z_{T_{v'}}(t_{k+1})) + bw_{T_{v'}} z_{T_{v'}}(t_{k+1}) \tag{5}$$

Given that activity types T_v and $T_{v'}$ are selected at times t_k and t_{k+1} , it must be that T_v yields a higher utility between t_k and t_{k+1} than any other activity type \hat{T}_v (Eq. (6)):

$$u_{T_v}(z_{T_v}(t)) + bw_{T_v} z_{T_v}(t) > \max_{\hat{T}_v \in \mathbf{L} \setminus T_v} u_{\hat{T}_v}(z_{\hat{T}_v}(t)) + bw_{\hat{T}_v} z_{\hat{T}_v}(t) \quad t_k \leq t < t_{k+1} \tag{6}$$

and $T_{v'}$ yields the highest utility at t_{k+1} (Eq. (7)):

$$u_{T_{v'}}(z_{T_{v'}}(t_{k+1})) + bw_{T_{v'}} z_{T_{v'}}(t_{k+1}) > \max_{\hat{T}_{v'} \in \mathbf{L} \setminus T_{v'}} u_{\hat{T}_{v'}}(z_{\hat{T}_{v'}}(t_k)) + bw_{\hat{T}_{v'}} z_{\hat{T}_{v'}}(t_k) \tag{7}$$

¹ In addition, it is worth highlighting that lifting the additive separability assumption for all activities except one (to retain a pivot between Eqs. (1) and (2)) would affect Eq. (3) by retaining consumption as a variable influencing the intensity and by including an additional term describing the marginal impact on consumption utility elsewhere. Thus the effect would be more at the conceptual rather than operational level, and hence we leave further exploration of this for future studies.

Now let us specify $V_{T_v \rightarrow T_{v'}}^{qk}$ as the indirect utility from Eq. (5) for an individual q in spell k as (Eq. (8)):

$$V_{T_v \rightarrow T_{v'}}^{qk} = \beta_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}^{qk} + \varepsilon_{T_v \rightarrow T_{v'}}^{qk} \tag{8}$$

where $X_{T_v \rightarrow T_{v'}}$ describes the vector of exogenous variables for individual q in spell k and the specific entry-exit combination $T_v \rightarrow T_{v'}$, $\beta_{T_v \rightarrow T_{v'}}$ is the vector of coefficients on these exogenous variables, and $\varepsilon_{T_v \rightarrow T_{v'}}^{qk}$ is a stochastic error term. Assume that this stochastic error term is independently and identically (*iid*) Type 1 extreme value (Gumbel)-distributed, with a scale parameter equal to unity, across the discrete alternatives, individuals, and spells. This assumption leads to a multinomial logit model (see Srinivasan and Bhat, 2005) expressing the probability that the entry-exit combination $T_v \rightarrow T_{v'}$ is chosen in spell k by an individual q (Eq. (9)):

$$P^{qk}(T_v \rightarrow T_{v'}) = \frac{\exp\left(\beta_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}^{qk}\right)}{\sum_{T_{\xi}} \sum_{T_{\xi'}} \exp\left(\beta_{T_{\xi} \rightarrow T_{\xi'}} X_{T_{\xi} \rightarrow T_{\xi'}}^{qk}\right)} \begin{matrix} T_v \left\{ \begin{array}{l} \in \mathbf{L} \setminus T_{v'} \text{ if } k = 1 \\ = T_{v'}^{k-1} \text{ if } k > 1 \end{array} \right. \\ T_{\xi} \left\{ \begin{array}{l} \in \mathbf{L} \setminus T_{\xi'} \text{ if } k = 1 \\ = T_{\xi'}^{k-1} \text{ if } k > 1 \end{array} \right. \\ T_{\xi'} \in \mathbf{L} \setminus T_{\xi} \end{matrix} \tag{9}$$

A number of additional observations can be made in respect to Eq. (9). Firstly, note that while the *iid*-Gumbel assumption in the current paper is for the sake of simplicity, it is straightforward to relax this assumption in order to capture more complex dependencies through more elaborate discrete choice structures. Secondly, observe that Eq. (9) explicitly forbids the exit state to be the same as the entry state (also recall the comment made in respect to Eq. (5) earlier in the section) which would be inconsistent with Eqs. (6) and (7). Thirdly, the possibility of multi-spell contexts makes it necessary to account for the fact that an exit activity type of the k^{th} spell will also be the $k + 1^{\text{th}}$ entry type. This can be done by placing an appropriate restriction on the choice sets of entry-exit combination types. This is crucial from the point of view of ensuring coherence in the sequence of choices made by the individual and thus avoiding estimation bias arising from considering alternatives that the individual is effectively not choosing.

What follows from such restrictions is that, when modelling the choice between only two activity types (as is the case in our empirical part later, i.e. work vs. non-work), the discrete component of activity choice is present only in reference to the first spell. Subsequent activity types are pre-determined in an alternating fashion as a consequence of the first spell's type. Whilst intuitive, this fact is worth noting as it can reduce the computational expense of the estimation process.

3.2.2. Duration component

For the duration modelling component, we make use of the hazard-based model, which to date has been employed extensively in the context activity duration modelling literature (Bhat, 2000), including jointly with an activity type choice (Srinivasan and Bhat, 2005). Recall that, based on the theoretical model in Section 3.1, and specifically Eq. (3), activity T_v is interrupted at time t when:

- there exists another activity type $T_{v'}$ which at that time yields higher utility V ;
- there has been no other activity $T_{v''}$ yielding higher utility since T_v started.

Thus, without loss of generality, assume that the spell k commences at $t_k = 0$, which simply means that t denotes the duration or spell-specific clock-time rather than general clock-time. Hence it is possible to define the probability $P_{T_v \rightarrow T_{v'}}$ of activity T_v lasting until t_{k+1} after which it switches to activity type $T_{v'}$ (omitting the individual- and spell-specific indices q and k for clarity):

$$P_{T_v \rightarrow T_{v'}}(t) = P\left[\left(\exists T_{v'} : V_{T_{v'}}(t_{k+1}) > V_{T_v}(t_{k+1})\right) \wedge \nexists(T_{v''} : V_{T_{v''}}(t) > V_{T_v}(t), t_k < t < t_{k+1})\right]_{T_{v'}, T_{v''} \in \mathbf{L} \setminus T_v} \tag{10}$$

In addition, activity duration is t_{k+1} given the assumption placed on t_k .

Eq. (10) provides a convenient link to a hazard-based formulation. Specifically, assume that the probability that utility of an alternative activity type $V_{T_{v'}}$ exceeds that of the present type (V_{T_v}) is distributed according to probability distribution with density $f_{T_v \rightarrow T_{v'}}$ and cumulative distribution function $F_{T_v \rightarrow T_{v'}}$. Thus, it is possible to define the hazard function $\lambda_{T_v \rightarrow T_{v'}}(t)$ which describes the risk of activity switching at time t , given that it has not switched so far:

$$\lambda_{T_v \rightarrow T_{v'}}(t) = \frac{f_{T_v \rightarrow T_{v'}}(t)}{1 - F_{T_v \rightarrow T_{v'}}(t)} = \lim_{h \rightarrow 0^+} \left[\frac{P(t \leq s_{T_v \rightarrow T_{v'}} \leq t + h | t \leq s_{T_v \rightarrow T_{v'}})}{h} \right] \tag{11}$$

Given that switching will depend on the relative attractiveness of both the activity that the person is currently involved in and one which he or she can switch to, it is necessary to define hazard functions for each specific combination of activity types, which coincides with the discrete alternatives from Section 3.1 (activity type combinations T_v and $T_{v'}$). These hazard functions can be specified, for an individual q and spell k , using the proportional hazard form of Kiefer (Kiefer, 1988; Srinivasan and Bhat, 2005):

$$\lambda_{T_v \rightarrow T_{v'}}^{qk}(t) = \lambda_{0T_v \rightarrow T_{v'}}^{qk}(t) \exp\left(-\gamma_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}^{qk}\right) \tag{12}$$

where $\lambda_{0T_v \rightarrow T_{v'}}$ is the baseline at time t , $X_{T_v \rightarrow T_{v'}}^{qk}$ is the vector of exogenous covariates characterising individual q during spell k , and $\gamma_{T_v \rightarrow T_{v'}}$ is the vector of corresponding coefficients. Note that the variables characterising the respondent can vary between spells which can, for example, express changing conditions of travel during the journey, e.g. crowding or availability of connectivity.

Bhat (1996) has shown that the formulation above can be stated as:

$$\begin{aligned} \hat{S}_{T_v \rightarrow T_{v'}}^{qk} &= \log \Lambda_{0T_v \rightarrow T_{v'}}^{qk} \left(s_{T_v \rightarrow T_{v'}}^{qk} \right) = \log \int_0^{s_{T_v \rightarrow T_{v'}}^{qk}} \lambda_{0T_v \rightarrow T_{v'}}^{qk}(t) dt \\ &= \gamma_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}^{qk} + \eta_{T_v \rightarrow T_{v'}}^{qk} \end{aligned} \quad (13)$$

where $\hat{S}_{T_v \rightarrow T_{v'}}^{qk}$ is spell-specific individual's q integrated hazard for the duration associated with a particular entry-exit combination $T_v \rightarrow T_{v'}$ and $\eta_{T_v \rightarrow T_{v'}}^{qk}$ is the stochastic error term following the extreme value distribution:

$$G(\eta) = 1 - \exp(-\exp(\eta)) \quad (14)$$

Now assume that the continuous time t is discretised into Π^q periods represented by index π^q :

$$\pi^q = 1 \text{ if } t \in (0, t^{q1}], \pi^q = 2 \text{ if } t \in (t^{q1}, t^{q2}], \dots, \pi^q = \Pi^q \text{ if } t \in (t^{q\Pi^q-1}, \infty) \quad (15)$$

Notice that we allow for the number and width of the intervals to be person specific, in contrast to the previous efforts where they were generic for the whole sample. This is crucial in order to account for situations in which the precision of the duration records varies across the individuals leading to potential heteroscedasticity issues. This can be the case, for example, if respondents are asked to report their time allocation using equal fractions of their travel ('What did you do during the first 10%, or a decile, of your journey time?'). In such instances, the precision of recording will be higher for shorter journeys. For instance, with decile recording, a 20 min journey will have 2 min intervals whilst a 3 h journey will have intervals 18 min long. The formulation above conveniently takes these differences into account by appropriately modifying the interval thresholds for each trip and respondent. In addition, the interval-based approach effectively accounts for lack of precise information regarding the exact duration of a spell, rather than imposes a particular assumption, e.g. the interval mid-point, that would be required for specifying the respective probability density function.

Bhat (1996) has further shown that the probability that the transition from activity T_v to $T_{v'}$ happens at time t during period $\pi^q = \kappa$ can be related to the integrated hazard from Eq. (13):

$$P_{T_v \rightarrow T_{v'}}^{qk}(\pi^q = \kappa) = P(t^{q\kappa-1} < t < t^{q\kappa}) = P\left(\log \Lambda_{0T_v \rightarrow T_{v'}}^{qk}(t^{q\kappa-1}) < \log \Lambda_{0T_v \rightarrow T_{v'}}^{qk}(t) < \log \Lambda_{0T_v \rightarrow T_{v'}}^{qk}(t^{q\kappa})\right) \quad (16)$$

When used in conjunction with Eq. (14), this provides a means of expressing $P_{T_v \rightarrow T_{v'}}^{qk}$ as a function of the covariates and the associated coefficients, and for a specific activity spell k :

$$P_{T_v \rightarrow T_{v'}}^{qk}(\pi^q = \kappa) = G\left(\log \Lambda_{0T_v \rightarrow T_{v'}}^{qk}(t^{q\kappa}) - \gamma_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}^{qk}\right) - G\left(\log \Lambda_{0T_v \rightarrow T_{v'}}^{qk}(t^{q\kappa-1}) - \gamma_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}^{qk}\right) \quad (17)$$

Coming back to Eq. (12), we assume a time-invariant baseline hazard while ensuring its positivity without placing restriction on the parameter for estimation $\gamma_{0T_v \rightarrow T_{v'}}$:

$$\lambda_{0T_v \rightarrow T_{v'}}^{qk}(t) = \exp(\gamma_{0T_v \rightarrow T_{v'}}) \quad (18)$$

Based on Eq. (13), this yields:

$$\log \Lambda_{0T_v \rightarrow T_{v'}}^{qk} \left(s_{T_v \rightarrow T_{v'}}^{qk} \right) = \log \int_0^{s_{T_v \rightarrow T_{v'}}^{qk}} \exp(\gamma_{0T_v \rightarrow T_{v'}}) dt = \log \left(s_{T_v \rightarrow T_{v'}}^{qk} \right) + \gamma_{0T_v \rightarrow T_{v'}} \quad (19)$$

and thus:

$$P_{T_v \rightarrow T_{v'}}^{qk}(\pi^q = \kappa) = G\left(\log \left(s_{T_v \rightarrow T_{v'}}^{qk} \right) + \gamma_{0T_v \rightarrow T_{v'}} - \gamma_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}^{qk}\right) - G\left(\log \left(s_{T_v \rightarrow T_{v'}}^{qk} \right) + \gamma_{0T_v \rightarrow T_{v'}} - \gamma_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}^{qk}\right) \quad (20)$$

On the other hand, right censoring can be accommodated by using the appropriate complementary probability, expressing the probability of not observing activity switching when the observation was censored.

In addition, the $\gamma_{T_v \rightarrow T_{v'}}$ parameters carry a further meaning, which can be shown by considering the so-called survival function $S_{T_v \rightarrow T_{v'}}$ associated with the hazard function (12). $S_{T_v \rightarrow T_{v'}}$ describes the probability of an episode lasting at least $s_{T_v \rightarrow T_{v'}}$ when switching to activity type $T_{v'}$ occurs is given by (Miller, 1998; Rodríguez, 2007):

$$\begin{aligned} S_{T_v \rightarrow T_{v'}}(t) &= P(t < s_{T_v \rightarrow T_{v'}}) = 1 - F_{T_v \rightarrow T_{v'}}(t) = \int_t^\infty f_{T_v \rightarrow T_{v'}}(g) dg \\ &= \exp\left(-\int_0^t \lambda_{T_v \rightarrow T_{v'}}(g) dg\right) = \lambda_{0T_v \rightarrow T_{v'}} t \exp(-\gamma_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}) \end{aligned} \quad (21)$$

This expression can be used to define the expected duration of the individual's q spell k of activity (Miller, 1998; Rodríguez, 2007):

$$E\left(s_{T_v \rightarrow T_{v'}}^{qk}\right) = \int_0^\infty t f_{T_v \rightarrow T_{v'}}(t | \gamma_{T_v \rightarrow T_{v'}}, X_{T_v \rightarrow T_{v'}}^{qk}) dt = \int_0^\infty S_{T_v \rightarrow T_{v'}}(t | \gamma_{T_v \rightarrow T_{v'}}, X_{T_v \rightarrow T_{v'}}^{qk}) dt = \exp\left(-\gamma_{0T_v \rightarrow T_{v'}} + \gamma_{T_v \rightarrow T_{v'}} X_{T_v \rightarrow T_{v'}}^{qk}\right) \quad (22)$$

Thus it can be shown that the estimated parameters $\gamma_{T_v \rightarrow T_{v'}}$ are semi-elasticities (Wooldridge, 2013), i.e. the percentage change in the expected duration of the spell in terms of a change (not percentage-wise) in factor $X_{T_v \rightarrow T_{v'}}^{qk} \in X_{T_v \rightarrow T_{v'}}^{qk}$:

$$\frac{\% \Delta E\left(s_{T_v \rightarrow T_{v'}}^{qk}\right)}{\Delta X_{T_v \rightarrow T_{v'}}^{qk}} \approx \frac{\partial \log E\left(s_{T_v \rightarrow T_{v'}}^{qk}\right)}{\partial X_{T_v \rightarrow T_{v'}}^{qk}} = \gamma_{T_v \rightarrow T_{v'}} \quad (23)$$

While the semi-elasticity is not unit-free, as compared to the traditional notion of elasticity, it does not require $x_{T_v \rightarrow T_{v'}}^{qk}$ to be a continuous variable in order to be meaningful. This is an important property when ascertaining the effect of discrete variables such as the presence of specific on-board facilities (e.g. table, Wi-Fi) or possession of ICT equipment, amongst others.

3.2.3. Productivity component

The final component of the framework is aimed at modelling the mean productivity reported by an individual as defined in Eq. (4). Without loss in generality, we suppress mode i and route j indices for clarity. We propose to model this mean productivity as a random variable distributed according to a log-normal distribution with mean μX^q and standard deviation σ_ζ :

$$\zeta^q = \frac{\sum_{T_k \in \mathbf{w}} \int_{t_k}^{t_{k+1}} z_{T_{kij}}(t, \psi, \theta) dt}{\sum_{T_k \in \mathbf{w}} (t_{k+1} - t_k)} \sim \log \text{Norm}(\mu X^q, \sigma_\zeta^2) \quad (24)$$

where ζ^q denotes the average productivity experienced by individual q , as previously in Eq. (4), X^q is a vector of the relevant exogenous covariates characterising the respondent and their trip, and μ is a vector of the corresponding coefficients. The assumption of log-normal distribution, which has been widely used in economics (e.g. Oulton, 2004, 1998; Shockley, 1957), ensures positive values of productivity without imposing any additional constraints on the estimated parameters μ and σ_ζ thus facilitating the estimation.

In the present context, the empirical data on productivity contains a self-reported assessment of productivity relative to that experienced under typical office conditions (see Section 4). We discretise the reported quantities into five discrete intervals, $\bar{\zeta}_{ij}^q$, bounded by their respective lower and upper cut-points $\bar{\zeta}^{LO}$ and $\bar{\zeta}^{UP}$ (Eq. (25)), so as to obtain cut-off points which round true values reported up to 3-decimal points into intuitive integer percentages, (i.e. 0.505 to 50%, 0.995 to 100%, etc.):

$$\begin{aligned} \bar{\zeta}^q &= 1 \text{ if } \zeta_{ij}^q \in (0, 0.505) \\ \bar{\zeta}^q &= 2 \text{ if } \zeta_{ij}^q \in [0.505, 0.995) \\ \bar{\zeta}^q &= 3 \text{ if } \zeta_{ij}^q \in [0.995, 1.005) \\ \bar{\zeta}^q &= 4 \text{ if } \zeta_{ij}^q \in [1.005, 1.505) \\ \bar{\zeta}^q &= 5 \text{ if } \zeta_{ij}^q \in [1.505, \infty) \end{aligned} \quad (25)$$

Such a discretisation results in reasonably intuitive categories:

- very low productivity, up to 50% of that under typical office conditions, i.e. $\bar{\zeta}^q = 1$,
- lower than usual office conditions, between 51 and 99%, i.e. $\bar{\zeta}^q = 2$,
- similar to office conditions, i.e. 100% $\bar{\zeta}^q = 3$,
- better than office conditions, between 101 and 150%, i.e. $\bar{\zeta}^q = 4$,
- super-productive, 151% and above, i.e. $\bar{\zeta}^q = 5$.

The reason for discretisation is two-fold. Firstly, it permits the use of a cumulative distribution function, denoted as F_ζ , which will become more apparent in the next section. Secondly, the interval-based approach is more robust in terms of accounting for potential inaccuracies in self-reporting and quantifying productivity by respondents. Hence, using Eqs. (24) and (25), it is possible to define the probability that an individual q reports productivity ζ_{ij}^q which falls into interval $\bar{\zeta}^q$ as:

$$P_\zeta(\bar{\zeta}^q) = F_\zeta\left(\zeta^q \leq \bar{\zeta}^{UP} | X^q, \mu, \sigma_\zeta\right) - F_\zeta\left(\zeta^q < \bar{\zeta}^{LO} | X^q, \mu, \sigma_\zeta\right) \quad (26)$$

Naturally, for the upper-most category the complementary probability can be used:

$$P(\bar{\zeta}^q = 5) = 1 - F_\zeta\left(\zeta^q < 1.505 | X^q, \mu, \sigma_\zeta\right) \quad (27)$$

Last but not least, the assumption of a log-normal distribution of productivity leads to:

$$\frac{\% \Delta E(\zeta^q)}{\Delta x^q} \approx \frac{\partial \log E(\zeta^q)}{\partial x^q} = \frac{\frac{\partial \log E(\zeta^q)}{\partial x^q}}{E(\zeta^q)} = \mu \tag{28}$$

which defines μ as the semi-elasticity of expected productivity with respect to a specific covariate $x^q \in X^q$, i.e. approximately the percentage change in the expected productivity as a result of a change (not percentage-wise) in x^q . This again facilitates benchmarking of the effects of the presence of different facilities against each other.

3.2.4. Joint model using copula approach

The fact that the model components described in Sections 3.2.1–3.2.3 arise from the same, underlying microeconomic framework suggests the need for joint estimation. To achieve this, we extend the joint activity-duration approach by Srinivasan and Bhat (2005) by also incorporating a productivity component. By the probability integral transform, cumulative distribution functions of a continuous distribution will follow a standard uniform distribution $U(0, 1)$. Thus based, on Eqs. (9), (20) and (23), it is possible to state:

$$P^{qk}(T_v \rightarrow T_{v'}) \sim U(0, 1) \tag{29}$$

$$P_{T_v \rightarrow T_{v'}}^{qk}(\pi^q) \sim U(0, 1) \tag{30}$$

$$P_\zeta(\overline{\zeta^q}) \sim U(0, 1) \tag{31}$$

Eqs. (29)–(31) can be used as inputs to formulate a copula, which offers a flexible way of modelling the interdependence between the components. A copula, C , is defined as a joint probability distribution over M random variables, $U_{1...M}$, each with a standard uniform marginal distribution, and with a set of parameters, Θ , characterising the dependency structure:

$$C(u_1, u_2, \dots, u_M) = P(U_1 < u_1, U_2 < u_2, \dots, U_M < u_M | \Theta) \tag{32}$$

Copulas have seen a wide range of applications in recent decades, including in travel behaviour studies (Bhat and Sener, 2009; Sener and Bhat, 2011). This has been due to their flexibility and wide applicability, based on the Sklar’s theorem (Nelsen, 2006), which states that any multivariate joint distribution can be expressed in the form of marginal distributions and a copula describing the dependence structure.

While multiple copulas exist (see Nadarajah et al., 2016, for a good summary), in the current context, we choose the Farlie–Gumbel–Morgenstern (FGM) copula C_{FGM} to model the dependence between the three components described in Eqs (29)–(31). An FGM copula for M random uniformly distributed variables is defined as:

$$C_{FGM}(u_1, u_2, \dots, u_M) = \prod_{m=1}^M u_m \times \left[1 + \sum_{m=1}^{M-1} \sum_{m'=m+1}^M \theta_{mm'}^{FGM} (1 - u_m)(1 - u_{m'}) \right] \tag{33}$$

where $\theta_{mm'}^{FGM}$ are dependence parameters, belonging to vector Θ^{FGM} , for each pairwise combination m and m' of the variables. The FGM copula has a number of properties that are convenient in the present context. Specifically, it can be easily extended to applications beyond two dimensions while still being able to characterise pairwise correlations through $\frac{M(M-1)}{2}$ dependence parameters, hence retaining substantial flexibility (Nelsen, 2006). At the same time, it still has a closed-form analytical expression enabling simulation-free direct maximum likelihood estimation (Bhat and Sener, 2009). This contrasts FGM copula with the Archimedean family of copulas where there is a potentially restricting single parameter dependence characterisation. On the other hand, more flexible multivariate Gaussian and Student’s t copulas do not have closed form expressions and rely on numerical integration, which can hamper parameter estimation, due to the computational expense and function approximations not being stable enough, especially for higher dimensions. Hierarchical and vine copula approaches (Okhrin and Ristic, 2014), on the other hand, could lead to prohibitively complex structures, especially with regards to the choice of structure and appropriate copulas at different levels.

Although FGM has a number of attractions, it is also necessary to be aware of the limitations of this approach. These are two-fold. Firstly, to ensure non-negativity of the joint density, the following restrictions need to be placed on the dependence parameters (Cambanis, 1977; Nelsen, 2006):

$$-1 \leq \theta_{mm'}^{FGM} \leq 1 \quad \forall m, m' \in M \tag{34}$$

and:

$$1 + \sum_{m=1}^{M-1} \sum_{m'=m+1}^M \theta_{mm'}^{FGM} \phi_m \phi_{m'} \geq 0 \quad \forall \phi_m, \phi_{m'} \in \{-1, 1\} \tag{35}$$

Condition (34) can be expressed equivalently in the following form:

$$\theta_{mm'}^{FGM} = \frac{2}{1 + \exp(\alpha_{mm'}^{FGM})} - 1 \quad \forall m, m' \in M \tag{36}$$

without any restrictions on $\alpha_{mm'}^{FGM}$ parameters to be estimated as $\alpha_{mm'}^{FGM} \in \mathbb{R}$ and Eq. (34) holds as a weak inequality.

Condition (35), on the other hand, is much more restrictive and can in principle hamper the empirical estimation process. In practice, however, its violation is not severe as long as the resulting copula values are far from the vertices of the M -dimensional $[0, 1]$ cube which, in general, is the case with the models applied in the present context (Bhat and Sener, 2009). In addition, the validity of the constraint can be examined directly post-estimation, given that $M=3$ in the current context. Hence we did not impose the restriction during the specification and estimation, but we verified it on the final parameters where we found it to be maintained given a number of parameters not being significantly different from zero.

The second limitation of FGM arises from its limited ability to capture dependence (correlation) between variables which is permitted in the interval of $[-2/9, 2/9]$ as measured by Kendall's tau (Nelsen, 2006, p. 162). If stronger dependence is suspected, it may be necessary to trade-off between retaining the FGM formulation and using a more flexible but also more complex and computationally expensive approach.

In the instances where there is, however, either no data regarding one of the components, e.g. productivity, or where its value remains constant, FGM copula would reduce to a bi-variate, single-parameter formulation. For such instances, we propose to use a Frank copula, which enables a much more flexible characterisation of the dependence (Trivedi and Zimmer, 2006), i.e. correlation in the interval of Kendall's tau of $[-1, 1]$. Thus, the bivariate Frank copula C_{FRA} equivalent of Eq. (33) is:

$$C_{FRA}(u_1, u_2) = -\frac{1}{\theta^{FRA}} \log \left[1 + \frac{(\exp(-\theta^{FRA}u_1) - 1)(\exp(-\theta^{FRA}u_2) - 1)}{\exp(-\theta^{FRA}) - 1} \right] \tag{37}$$

with the dependence parameter $\theta^{FRA} \in \mathbb{R} \setminus \{0\}$.

Using Eqs. (29)–(31) together with the copula formulation (33), it is possible to define the joint probability of observing individual's q spell k which is of activity type T_v and transiting to $T_{v'}$ in period π^q and with mean productivity in interval ζ^q :

$$L^{qk}(T_v \rightarrow T_{v'}, \pi^q, \zeta^q) = C_{FGM} \left(P^{qk}(T_v \rightarrow T_{v'}), P_{T_v \rightarrow T_{v'}}^{qk}(\pi^q), P_\zeta(\zeta^q) | \Theta_{T_v \rightarrow T_{v'}}^{FGM} \right) \tag{38}$$

where $\Theta_{T_v \rightarrow T_{v'}}^{FGM}$ is a vector containing the dependence parameters. If information on productivity is not available or the reported productivity is constant, Eq. (37) can be used to arrive at the corresponding expression with the respective dependence parameter $\theta_{T_v \rightarrow T_{v'}}^{FRA}$:

$$L^{qk}(T_v \rightarrow T_{v'}, \pi^q) = C_{FRA} \left(P^{qk}(T_v \rightarrow T_{v'}), P_{T_v \rightarrow T_{v'}}^{qk}(\pi^q) | \theta_{T_v \rightarrow T_{v'}}^{FRA} \right) \tag{39}$$

Note that Eqs. (38) and (39) describe situations in which the activity spell is uncensored, i.e. wholly contained within the journey so that the exit state was known. If the spell is adjacent to the end of the journey, i.e. $k=K$, its interruption by the journey end is exogenous rather than resulting from the same mechanism as prior transitions, driven by Eq. (3). This has two effects. Firstly, it needs to be accounted for in the duration component through right censoring (Hensher and Mannering, 1994). Secondly, by definition, the exit activity type of the last spell is unknown and hence it is necessary to consider all possible exit types in both the tri-variate:

$$L_C^k(T_v, \pi^q, \zeta^q) = \sum_{T_{v'} \in \mathbf{T} \setminus T_v} C_{FGM} \left(P^{qK}(T_v \rightarrow T_{v'}), P_{T_v \rightarrow T_{v'}}^{qK}(\pi^q), P_\zeta(\zeta^q) | \Theta_{T_v \rightarrow T_{v'}}^{FGM} \right) \tag{40}$$

and bivariate formulations:

$$L_C^k(T_v, \pi^q) = \sum_{T_{v'} \in \mathbf{T} \setminus T_v} C_{FRA} \left(P^{qK}(T_v \rightarrow T_{v'}), P_{T_v \rightarrow T_{v'}}^{qK}(\pi^q) | \theta_{T_v \rightarrow T_{v'}}^{FRA} \right) \tag{41}$$

when modelling the respective joint probability for the last spell.

Eqs. (38)–(41) enable construction of the likelihood \mathcal{L} for the sample of N respondents, with each respondent q with K_q spells (episodes):

$$\begin{aligned} \mathcal{L} = & \prod_{q=1}^N \prod_{k=1}^{K_q} \prod_{\pi=1}^{\Pi_q} \prod_{T_v=1}^L \prod_{T_{v'}=1}^{L \setminus T_v} \left(\left[\left(L^{qk}(T_v \rightarrow T_{v'}, \pi) \right)^{1-\delta_C} \left(L_C^k(T_v, \pi) \right)^{\delta_C} \right]^{1-\delta_{FGM}} \right. \\ & \left. \times \left[\prod_{\zeta=1}^5 \left(\left[L^{qk}(T_v \rightarrow T_{v'}, \pi, \zeta) \right]^{1-\delta_C} \left(L_C^k(T_v, \pi, \zeta^q) \right)^{\delta_C} \right)^{\delta_{FGM}} \right]^{\delta_k \delta_{\pi q} \delta_{T_v} \delta_{T_{v'}}} \right) \end{aligned} \tag{42}$$

with the following indicator variables:

$$\delta_{FGM} = \begin{cases} 1 & \text{if the FGM (tri - variate) copula is to be used,} \\ 0 & \text{otherwise;} \end{cases}$$

$$\begin{aligned}
\delta_C &= \begin{cases} 1 & \text{if } k_q \leq K_q, \text{ i.e. the journey end occurs during the episode and censoring applies,} \\ 0 & \text{otherwise;} \end{cases} \\
\delta_k &= \begin{cases} 1 & \text{if } k \leq K_q, \\ 0 & \text{otherwise;} \end{cases} \\
\delta_\pi &= \begin{cases} 1 & \text{if the duration of the spell falls within time interval } \pi, \\ 0 & \text{otherwise;} \end{cases} \\
\delta_{T_v} &= \begin{cases} 1 & \text{if the current episode (entry type) is an activity of } T_v \text{ type,} \\ 0 & \text{otherwise;} \end{cases} \\
\delta_{T_{v'}} &= \begin{cases} 1 & \text{if the subsequent (exit) episode is of } T_{v'} \text{ type or the episode is censored,} \\ 0 & \text{otherwise;} \end{cases} \\
\delta_{\bar{\zeta}} &= \begin{cases} 1 & \text{If the reported productivity falls into interval } \bar{\zeta}, \\ 0 & \text{otherwise.} \end{cases}
\end{aligned}$$

In addition, the following constraints must be maintained so as to ensure that the exit activity type of the k th episode is the same as the entry type for episode $k+1$ th:

$$T_{v'}^{k_q} = T_v^{k+1_q} \quad 1 \leq k_q \leq K_q - 1 \quad (43)$$

The parameters to be estimated are at most, i.e. assuming no restrictions:

- $\#(\mathbf{L}) \times \#(\mathbf{L} - 1) \times \#(X_{T_v \rightarrow T_{v'}})$ activity type choice parameters β associated with covariates $X_{T_v \rightarrow T_{v'}}$;
- $\#(\mathbf{L}) \times \#(\mathbf{L} - 1) \times \#(\gamma_{T_v \rightarrow T_{v'}})$ hazard model parameters γ associated with covariates $X_{T_v \rightarrow T_{v'}}$;
- $\#(\mathbf{L}) \times \#(\mathbf{L} - 1)$ baseline hazard parameters $\gamma_{0T_v \rightarrow T_{v'}}$;
- $\#(\mathbf{L}') \times \#(\mu)$ productivity parameters μ associated with covariates X ;
- $\#(\mathbf{L}') \times \#(\mu)$ productivity distribution scale (standard deviation) parameters σ_ζ ;
- $\#(\mathbf{L}') \times \#(\mathbf{L} - 1) \times \#(\Theta^{FGM})$ dependence parameters $\widehat{\Theta}^{FGM}$;
- $[\#(\mathbf{L}) - \#(\mathbf{L}')] \times [\#(\mathbf{L}) - 1]$ dependence parameters θ^{FRA} ,

where $\#(\cdot)$ denotes the cardinality of a set or length of a vector, \mathbf{L}' denotes the set of activity types for which the productivity component is modelled. Given the closed-form expression of the likelihood expression (42), standard direct maximum likelihood estimation (MLE) approaches can be used.

4. Empirical context and data

In this paper we employ data from the 2008 Study of the Productive Use of Rail Travel-time (SPURT), which surveyed 1660 business passengers on a number of rail routes in the United Kingdom, in March and April 2008 (DfT, 2009). A detailed description of the data collection process can be found in the official report produced from the SPURT study (DfT, 2009). Overall, data collected from 940 respondents and including 2606 activity spells, were complete enough to be used in the estimation. Table 1 presents a number of summary statistics concerning the initial activity choice, duration data, and productivity as reported in the survey.

In the present context, we used questions from the survey that asked respondents about the following aspects:

- the characteristics and context of the trip, e.g. duration, purpose, ticket type, class and cost of travel, seating availability, crowding, transport modes to and from the station, presence of companions;
- presence of on-board facilities: table, power socket, and Wi-Fi;
- attributes of the respondent: gender, age, employment status, personal income;
- use of ICT: laptop, mobile phone, portable digital assistant (PDA);
- activities undertaken immediately prior to the journey, e.g. phone calls, laptop use;
- journey time allocation between work and non-work activities;
- work-related productivity relative to that in typical office conditions;
- attitude towards the prevailing crowding conditions, productive use of travel time, intention to spend travel time, willingness to reduce work time if travel time shorter.

Note that given that only two types of activities (work and non-work) were reported on in terms of the time allocation, the activity type (discrete choice) component effectively reduces to the choice of initial activity. The remaining types of episodes are effectively pre-determined by the initial one given the conditions imposed on the choice set in Eq. (9).

As for the travel time allocation, the way in which respondents were asked to record their work-related activities was to mark suitable sections of a bar dividend into ten equal sections, and representing the total duration of the journey (Fig. 2):

Naturally, this method of recording introduces potential uncertainties regarding when, within the section, an episode commenced and when it ended. In the current example we make an assumption that the first and last 10% of the journey were spent entirely in the activities indicated by the respondents, i.e. in the example in Fig. 2 both intervals were spent working. It would be possible to account for the option of existence of short episodes at the beginning and end of the

Table 1

Summary statistics of the SPURT sub-sample used in the estimation ($N = 940$, episode spells = 2606).

	Count	Percentage		
Initial activity choice				
Work	382	40.6%		
Non-work	558	59.4%		
All	940	100%		
	Min.	Max.	Mean	Std. dev
^a Total activity duration (min)				
Work	0	247.2	57.0	39.1
Non-work	0	261	35.1	33.5
All	10	360	92.1	49.1
Number of spells (count)				
Work	0	4	2.0	1.2
Non-work	0	4	1.6	0.8
All	1	8	2.8	1.1
^a Spell duration (min)				
Work	1	247.2	60.3	43.4
Non-work	1	236	22.2	24.1
All	1	247.2	30.0	32.9
^b Work-related productivity				
	0.063	7.667	0.988	0.385

^aBased on the assumption of entire deciles allocated to particular activities. See discussion later in this section;

^bRespondents with at least one work spell

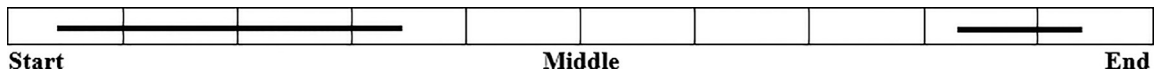


Fig. 2. Example of time allocation record in the SPURT survey: the marking indicates segments allocated to work activities. Source: DfT, 2009.

trip, although this would involve making further assumptions regarding the likelihood of the existence of such episodes. On balance, such an approach would at best only partially address the issue and would do so at the expense of unnecessary complexity and possible bias in the baseline hazard should the assumption not hold. It is useful, however, to make a recommendation that future use of the duration recording mechanism similar to that outlined in Fig. 2 should be accompanied by questions concerning initial and final activity types.

For other episodes, it is necessary to consider upper and lower bounds: activities covering two fields in Fig. 2 could last between a single instant (for numerical reasons 1 minute is assumed) and up to, but excluding 12 min for a 60 min journey. Thus a record such as that in Fig. 2, and assuming a total journey duration of 60 min would be coded as the following sequence of episodes:

- first work episode with duration between 18 to 24 min;
- first non-work episode with duration between 24 and 36 min;
- second work episode with duration of between 6 and 12 min. In this case, however, censoring needs to be applied given that the spell was the final one (recall Eqs. (40) and (41)).

Naturally, the decile-based recording makes the precision and hence the associated error, a function of the journey duration, indicating the risk of heteroscedasticity. Nevertheless, as shown in Section 3.2.2, the appropriate respondent-specific adjustment in the width of discrete intervals π^q ensures that this direct dependence on journey duration is accounted for, and the data can be used as input to the estimation procedure outlined in Section 3.

As for the reported productivity, the respondents were asked about the difference in the time required to accomplish the same work output that they did while travelling but under typical office conditions. This value was used to construct a measure of relative productivity as a ratio between the stated duration in office conditions, and the actual duration of work while travelling.

Regarding the set of attitude and experience questions, the following ones were asked of the respondents (DfT, 2009):

- the impact of the prevailing crowding conditions: ‘Did the level of crowding have any impact on the work you undertook or wished to undertake on the train?’;
- intention to spend travel time on non-work activities: ‘Have you or do you intend to do any of the following on this train? Working/studying unrelated to employment (reading/writing/typing/thinking), talking to other passengers - personal social, text messages/phone calls - personal/social, eating/drinking, leisure activity (playing games/reading/listening to music/radio), relaxing (sleeping/snoozing/window gazing/people watching), being bored, being anxious about journey (e.g. delays or where to get off), planning onward or return journey’;

- importance of productive use of travel time in making the mode choice: 'Do you agree with the following statement: I choose to travel by train and valued the fact that I can work on the train.';
- propensity to reduce work time if travel time shorter: 'Do you agree with the following statement: If the train journey was shorter I would reduce the amount of work I do on the train.'

While the questions above allowed for a set of different responses to each question, in the present context we collapsed them to binary variables to reduce the dimensionality and complexity of the estimation problem, especially with the already considerable set of parameters to estimate and limited sample size. We thus leave the possible extension for the future efforts.

In the present context, work-related activity was modelled using the FGM formulation, given the availability of the productivity variable. The non-work activity was modelled using the Frank copula. Hence the likelihood function could be formulated using Eq. (42). The standard direct MLE approach could thus be followed, which was implemented in R 3.2.1 using optimisation routines from the 'optimx' package, version 2013.8.7 (Nash et al., 2015).

5. Empirical results and interpretation

Estimation results are presented in Table 2. In the final specification we sought parsimony by including only variables that were statistically significant at the 10% level or higher. The final likelihood of the model of -6760.855 translates into an adjusted $\rho^2 = 0.171$, i.e. when compared against the likelihood at constants (market shares) only. The value is comparable to other travel models utilising copulas for joint models, e.g. Sener and Bhat (2011). In addition, we note the substantially improved fit of the joint model compared to one assuming independence between the components. Specifically, the increase in the log-likelihood from -6766.832 to -6612.991 is statistically significant ($p < .01$) as indicated by the likelihood ratio test statistic of 307.682 with 4 degrees of freedom (number of copula parameters).

As for the effects of covariates, we identify broadly four groups of variables influential in shaping time use and productivity patterns of travel time use. These can bear significant association with the probability of choosing work as the initial activity, expected duration of work or non-work episodes, or work-related productivity, as represented by the columns in Table 2. Recall also that the parameter values associated with duration and productivity represent semi-elasticity, as discussed in Sections 3.2.2 and 3.2.3. We discuss those groups in Sections 5.1–5.4, followed by a discussion of the dependence parameters in Section 5.5.

5.1. Journey context

The first group of covariates captures the effects of the context in which the trip takes place as well as the conditions prevailing during the journey. Among those we find the presence of a table to be positively associated with higher reported productivity, on average by 6.2%, perhaps by creating a more work-friendly milieu. At the same time, those respondents travelling in first class or with work-related destinations, were less likely to report work as the initial activity but, on the other hand, reported shorter spells of non-work activity. This pattern can reflect taking the opportunity to settle down which is then followed by work with shorter breaks.

We have also found that respondents on return legs tended to report lower productivity, on average by 4.5%. This is an intuitive finding, probably reflecting exhaustion from participation in the destination activities or because there tends to be a naturally lower incentive to work after the main purpose has been concluded (as compared to an outward leg which may involve preparatory work). In addition, we notice that those travellers who used season tickets as well as those travelling with companions, were more likely to report work as the initial activity. In the former instance, more regular travel might have made the respondent better prepared to engage in work while travelling more quickly and effectively. In the latter case, the presence of a colleague could be a motivating factor to either conduct work-related conversation, or stay engaged in work activity. Unfortunately, no information regarding the relationship to the companion was available which could perhaps shed additional light on the effect of the relationship, professional or social, to the companion.

In terms of the journey duration, we observe that durations between 45 and 90 min were associated with the respondents being more likely to have work as their initial activity as compared to either shorter or longer trips. This seemingly nonlinear effect could reflect two mechanisms. On the one hand, in the case of shorter trips, the necessity and effort required to set-up the working environment could discourage individuals from working at all. On the other hand, longer trips may provide a more relaxed context given more availability of time, and hence less pressure to have to engage in work immediately. The absence of total journey duration effect in the duration models implies similarity of spell durations across different journey durations. In addition, this indicates that more spells tend to be observed during longer journeys *ceteris paribus*.

When it comes to the cost of travel, those reporting more expensive ticket prices were also more likely to engage in work initially, but would also report longer spells of non-work. Given the demand-driven pricing system in the UK, higher cost could indicate travelling on busier services as we control for the class and duration. The parameters can thus reflect the propensity to finish any work-related tasks as soon as possible in order to hedge against the possibility of more disruptive conditions later in their journey.

We also observe the importance of the modes of transport used to travel from the station. Specifically, we observe that individuals who travelled from the station using car or taxi reported 7.1% and 4.1% higher productivity. This effect may

Table 2
Model estimation results (N = 940, episode spells = 2606).

	Work as initial activity		^a Work duration		^a Non-work duration		Productivity	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
<i>Journey context</i>								
Presence of a table	**0.062	0.026
First class	***-.505	0.162	.	.	**-.465	0.183	.	.
Return leg	***-.045	0.016
Work-related destination	**-.294	0.121	.	.	**-.307	0.139	.	.
Season ticket	**536	0.239
Journey cost (£00s)	*.360	184	.	.	*.374	0.217	.	.
Journey duration between 45 and 90 mins	**233	0.099
Mode of travel from the station: car	.	^b Fixed	***.071	0.019
Mode of travel from the station: taxi	.	^b Fixed	**0.041	0.020
Presence of a companion	**324	0.141
<i>Respondent attributes</i>								
Senior managerial position	**265	0.111	***.161	0.057
Gender: female	**-.280	0.119
<i>ICT</i>								
Used laptop	.	^b Fixed	***.283	0.056	*-.232	0.120	**-.034	0.017
Used laptop and income (£00,000s p.a.)	.	^b Fixed	***.098	0.026
Used laptop prior to the current leg	.	.	*-.251	0.145
Used a mobile phone	.	^b Fixed	***-.234	0.061
Female respondent using a mobile phone	.	^b Fixed	***.281	0.076	**-.388	0.163	.	.
Used mobile phone and presence of Wi-Fi	.	^b Fixed	**-.277	0.117
Used mobile phone prior to the current leg	.	.	**148	0.065
Used PDA	.	^b Fixed	.	.	***-.396	0.122	.	.
<i>Attitudes and experience</i>								
Considered crowding level disruptive	.	^b Fixed	***-.085	0.018
Intention to undertake non-work activities	.	.	***-.426	0.068	***.804	0.149	.	.
Would not reduce amount of work if the journey was shorter	**323	0.136	**-.123	0.056	***.759	0.160	.	.
<i>Structural parameters</i>								
Constant/ log(baseline hazard)	***-.368	0.155	-.121	0.085	0.162	0.191	***-.119	0.027
Scaling parameter (standard deviation)	1.000	Fixed	***.786	0.095	***1.761	0.164	***.222	0.004
Goodness of fit								
Log-likelihood with constants only: -7973.980 Log-likelihood without copulas: -6766.832 Log-likelihood at convergence: -6612.991 ρ^2 : 0.171								
AIC: 13,313.982								
Excluded variables ($p > .100$)								
<ul style="list-style-type: none"> • Service type (urban, interregional) • Proportion of travel seated • Power socket available • Home/non-home based trip 	<ul style="list-style-type: none"> • Worked just before the leg • Mode of travel to the station (any) • Mode of travel from the station: train, bus, walking, bicycle 	<ul style="list-style-type: none"> • Time of day departure • Use of laptop or PDA and presence of Wi-Fi • Age • Employment status 	<ul style="list-style-type: none"> • Choice of train on the grounds of being able to work while travelling 					

Note: "." indicates that the parameter was fixed at zero, and not estimated.

^aExpected value – recall Eq. (31);

^bNo estimation of the initial activity component given that the variable was based on what happened after the choice

*** $p \leq .010$ ** $p \leq .050$ * $p \leq .100$

reflect the more favourable reporting on travel conditions when more convenient egress modes were used, creating an overall better experience.

At the same time, we do not observe significant effects associated with service type (urban, interregional), proportion of travel seated, availability of power sockets, trip being a home- based trip, reporting to work immediately before the leg, mode of travel to the station, use of bus, train, bicycle or walking from the station or time of day departure.

5.2. Respondent attributes

The next group of factors are those describing the travellers themselves. Among these, we observe that respondents with senior managerial positions were more likely to engage in work activity initially as well as reported longer spells of work. This finding is reasonably intuitive as people with more responsibilities would be expected to have a higher propensity to engage in work and spend more time working.

Another respondent attribute which we found to have a statistically significant effect was that of lower propensity to engage in work initially by female respondents. The effect does not have a ready interpretation, perhaps beyond that of displaying a different preference for time allocation across genders.

While we have not found any significant effects associated with age or employment status (full-time as compared to part-time or self-employment), we have found income and gender to interact with ICT variables, which we report on in the subsequent section.

5.3. ICT

The third set of factors includes those associated with the use of Information and Communication Technologies, and in particular laptops, mobile phones, PDA, and Wi-Fi.²

Regarding the use of laptops, we observe that those respondents who reported their use had, on average, 28.3% longer work-related spells and 23.2% shorter non-work spells. We interpret this as reflecting the crucial role of laptops in enabling mobile work practices. We observe, however, that laptop users reported 3.4% lower productivity on average, as compared to those who did not use it. A possible interpretation of this effect could be related to the need for connectivity to fully capitalise on the laptop use, and perceived lower productivity in the conditions of very limited, low bandwidth, intermittent reception and mostly paid rather than free connectivity. Hence the substantial reliance on online resources and services by workers using laptops and inability to make use of these might have hampered the perception of productivity when compared to office conditions. Another interesting effect we have found concerns the positive association between income and productivity among laptop users. Recalling the semi-elasticity interpretation of the parameters, as per Eq. (28), we observe 9.8% higher productivity reported for each £10,000 of personal income. Finally, those individuals who used laptops just before their travel reported shorter durations of work. This could reflect that those respondents managed to accomplish their activities beforehand. This effect of pre-journey activity, as well as that of egress modes, as reported in Section 5.1, provides empirical evidence for the need to consider travel time use in the wider context of pre- and post-trip activities, as indicated in the conceptual model in Section 3.1.

Another set of effects has been observed in relation to the use of mobile phones. On its own and in the presence of Wi-Fi, this tended to be associated with shorter work episodes. This can be interpreted as resulting from possible disruption to tasks brought by unexpected messages and calls on the one hand, and opportunities to procrastinate through, e.g. accessing non-work content or personal communications on the other. Such effects are observed less among female respondents (the coefficients cancel out) who, furthermore, reported shorter non-work episodes. In addition, mobile phone users who used their phones immediately prior to the leg tended to report longer spells of work. In this instance, it could be possible that the prior communications were associated with discussing tasks to be accomplished while the respondent was travelling, especially given the intermittent phone reception on trains.

The final effect that we observe in the sample involves that of shorter durations of non-work episodes among the respondents who used a portable digital assistant, or PDA. While these devices have been largely replaced by modern portable devices (smartphones, tablet computers), the present finding can reflect the intuitive correlation between the use of work-dedicated devices and the reduced allocation of time to non-work activities.

5.4. Attitudes and experience

The final set of covariates captures the role of attitudes and experience. As expected, we find that respondents who considered the prevailing crowding levels disruptive also reported lower productivity, on average by 8.5%. We interpret this as evidence for consistency between reporting on the crowding being disruptive experiencing lower productivity.

² While we notice that the estimated coefficients associated with the effects of ICT lead to meaningful and intuitive interpretations, we note that they must be treated with caution, bearing also in mind that the data come from 2008. Since then, the ICT sector has seen major changes in terms of mobile ICT: mass adoption of smartphones (Apple's iPhone was released in the UK in November 2007 only), or introduction of tablet computers (Apple's iPad was introduced in 2010).

Table 3Estimated copula parameters and the associated dependence measures ($N=940$, episode spells = 2606).

	Copula	Dependence parameter	SE	Kendall's Tau	Spearman's rank correlation coefficient
<i>Work</i>					
Activity choice and interruption hazard	FGM (3-variate)	**-.743	0.346	-0.165	-0.248
Activity choice and productivity	FGM (3-variate)	-0.913	0.639	-0.203	-0.304
Activity interruption hazard and productivity	FGM (3-variate)	0.059	0.121	0.013	0.020
<i>Non-work</i>					
Activity choice and interruption hazard	Frank	***14.788	1.924	0.760	0.928

*** $p \leq .010$ ** $p \leq .050$ * $p \leq .100$

At the same time, we observe that respondents stating an intention to spend their travel time on various non-work activities indeed tended to report shorter work and longer non-work spells. We also observe that those respondents who claimed that they would not have reduced the amount of their work if the journey had been shorter reported shorter work spells and longer non-work spells. This could reflect the overall fixed and relatively limited amount of work, hence requiring less time, which would not be affected by a reduced journey time.

Last but not least, we do not observe any significant differences in time allocation patterns among respondents who stated that their choice of train was on the grounds of being able to work while travelling.

5.5. Dependence parameters

The final set of empirical findings include the copula parameters which describe dependence between activity type choice, duration, and, in the case of work activity, productivity (see Table 3). While the parameters are in general copula-specific, and thus cannot be compared across different copulas, they can be conveniently transformed into Kendall and Spearman rank correlation coefficients (Mahfoud, 2012; Nelsen, 2003, 2006; Wawrzyniak, 2006).

In the case of work activity, we observe a negative correlation between activity choice and duration. Recall that in the current, two activity-types case, the activity choice component effectively captures just the initial activity type choice, with the remaining choices being pre-determined. Hence the meaning of the estimated parameter is such that the unobserved factors which increase the choice of work initially are also associated with a decreased hazard of work interruption, and hence longer expected duration of work spells.

On the other hand, we do not observe the dependence parameters between activity choice and productivity, or activity duration and productivity, to be significantly different from zero. We interpret this as reflecting the possibility of a multi-faceted relationship between work choice, duration and intensity (productivity), possibly depending on the nature of the duties, tasks and their urgency. For example, with a higher urgency, higher productivity would also mean higher probability of work and also longer duration. Yet, without a defined and urgent task, an individual can perhaps be less likely to engage in work, but if so, these episodes can be creative and benefiting from a more relaxed, detached creative milieu. Those cases would seem to be reflected in the opposite signs of the dependence parameters. Exploring the existence of such effects, perhaps by investigating the set of tasks and their urgency, is certainly a direction warranting further research.

When it comes to non-work activity, we observe a positive correlation between the unobserved factors affecting activity choice and hazard of interruption, and hence negative correlation with activity duration. In other words, when non-work activity is chosen at first, the non-work spells tend to be shorter *ceteris paribus*. This can reflect the need of respondents to first settle down, relax, set up their environment, and only then engage in less interrupted work spells.

6. Conclusions

Developments in ICT continue to be significant determinants of how travel time is spent and experienced. Similarly, the rapid progress in vehicle automation requires a revised way of perceiving travelling, certainly moving away from the conventional notion of wasted driving time, to a period filled with activities, potentially productive and enjoyable.

In the present study, we propose a novel and unified way of conceptualising and modelling time allocation jointly with productivity. Specifically, we show that the PPS framework can be linked to a flexible econometric formulation which can incorporate any number of activity types, spells and productivity indicators. To date, such a comprehensive framework has not been available, restricting the ability to understand how various factors, ranging from journey context and conditions, to on-board facilities and ICT, to respondent attributes, may shape the allocation of travel time to different activities, including work, and the associated productivity.

In addition, our framework has a number of desirable properties for utilisation in policy and industrial settings. Firstly, its duration and productivity parameters can be readily interpreted as semi-elasticities, and remain unaffected by joint estimation which follows from the property of copula formulation. Secondly, incorporation of the discrete choice component

permits estimation of the willingness-to-pay for particular attributes characterising the discrete activity types. An example of such could be access to faster or more reliable Wi-Fi which could then be interpreted in relation to the implications for activity duration as well as productivity.

Thirdly, the framework can be conveniently employed in the context of the valuation travel time savings and hence the appraisal of the investments in transport infrastructure, where consideration of travel time quality may be important. Such contexts could include provision of on-board facilities for passengers or measures to reduce crowding. In particular, the current operationalisation in an empirical context complements the prior conceptual contribution of the PPS framework, thus offering a credible framework for microsimulation of travel time use and productivity. This, additionally, can serve as a means of inferring the parameters in the HE at both aggregate and disaggregate levels. Overall, such an approach would begin to more comprehensively and explicitly acknowledge the role of factors affecting quality and productivity of travel time, thus moving away from the current approach which captures such effects implicitly, e.g. through uplifts of demand or reductions in travel time coefficients in modal choice models.

Last but not least, our formulation can be implemented with a reasonably straightforward survey of time allocation using decile notation. Hence, its redeployment in other contexts and perhaps extended to more activity types will not be problematic.

While our empirical study is placed in the context of rail travel, where significant debate exists regarding the role of travel time use and productivity in the valuation of travel time savings and investment appraisal, our methodology can be readily employed in other transport contexts. For example, it can help in understanding the demand for on-board use of ICT and connectivity which has recently been driving safety discussions within aviation authorities across the globe. Beyond that, our framework could see application in the field of vehicle automation where it could provide a means to understand the economic and social implications resulting from converting driving time into work and other activities. This would complement growing research on supply-related implications, e.g. network capacity.

Our findings can also be informative for vehicle design. Specifically, while in the current effort we use productivity as a measure of activity intensity, it is possible to extend the approach to satisfaction, comfort and other measures of experience. Such a joint approach could help in achieving more optimal designs for specific customer types and their desired productivity and well-being implications. Last but not least, employers and their corporate travel agents could seek to optimise their mobile workforce performance by looking for travel arrangements to maximise the desired performance measures.

Naturally, our present contribution highlights some potential avenues for further research. Given the increased importance of mobile digital activities, future studies should improve on activity categorisation and level of information on ICT use, which at present appears too hardware- and not sufficiently task-centric. Similarly the question of productivity warrants exploration, especially in terms of how it should be measured in travel contexts so as to capture benefits for a wider range of occupations. Finally, we acknowledge that our empirical results are contextual, with the findings possibly specific to the study area, mode of transport, passenger segment (business) and time of data collection (crucial in light of the quickly evolving ICT). Hence further studies seeking to validate our framework in different contexts such as the one outlined above are warranted.

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