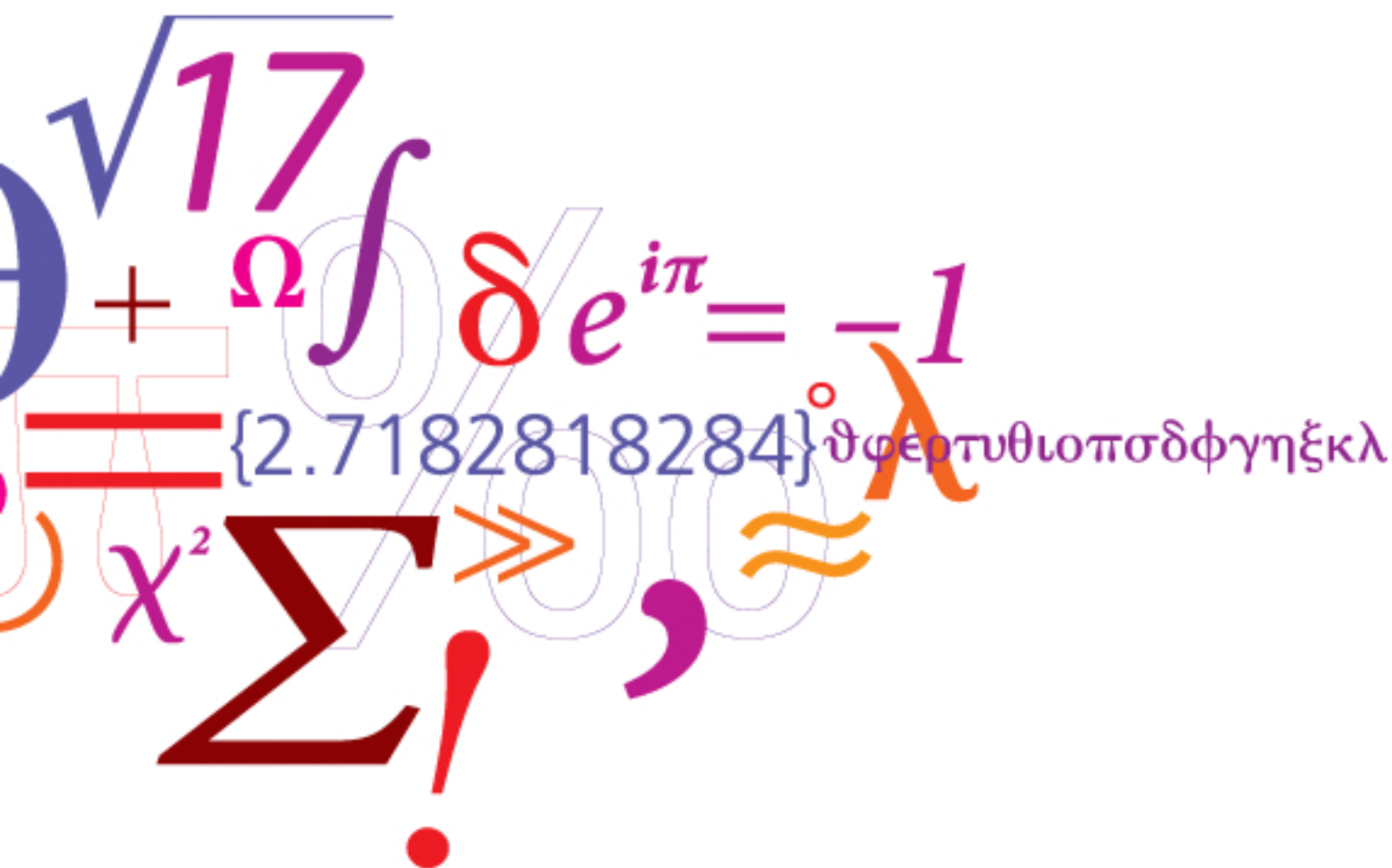


Departure Time Choice: Modelling Individual Preferences, Intention and Constraints

PhD Thesis



Mikkel Thorhauge
August 2015



DEPARTURE TIME CHOICE: MODELLING INDIVIDUAL PREFERENCES, INTENTION AND CONSTRAINTS

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PREFACE

This PhD thesis entitled *Departure Time Choice: Modelling Individual Preferences, Intention and Constraints* is submitted to meet the requirements for obtaining a PhD degree at the Department of Transport, Technical University of Denmark. The PhD project was supervised by Jeppe Rich, Associate Professor at DTU Transport, and co-supervised by Elisabetta Cherchi, Associate Professor at DTU Transport. The thesis consists of the chapters listed in the table of content and the papers listed below.

- Paper 1: Thorhauge, M., Cherchi, E., Rich, J., 2014, Building Efficient Stated Choice Design for Departure Time Choices using the Scheduling Model: Theoretical Considerations and Practical Implementations. Submitted to *Selected Proceedings from the Annual Transport Conference at Aalborg University, ISSN 1603-9696*, Trafikforskningsgruppen, Aalborg University.
- Paper 2: Thorhauge, M., Cherchi, E., Rich, J., 2015, How Flexible is Flexible? Accounting for the Effect of Rescheduling Possibilities in Choice of Departure Time for Work Trips. Resubmitted to *Transportation Research Part A: Practice and Policy*.
- Paper 3: Thorhauge, M., Haustein, S., Cherchi, E., 2015, Social Psychology meets Microeconometrics: Accounting for the Theory of Planned Behaviour in Departure Time Choice. Resubmitted to *Transportation Research Part F: Traffic Psychology and Behaviour*.
- Paper 4: Thorhauge, M., Cherchi, E., Rich, J., 2014, The Effect of Perceived Mobility Necessity in the Choice of Departure Time. Proceedings of the *Transportation Research Board (TRB) 93rd annual meeting*, Washington, USA, January 12-16, 2014.
- Paper 5: Thorhauge, M., Cherchi, E., Walker, J., Rich, J., 2015, The Role of Intention as Mediator between Latent Effects and Current Behavior: Application of a Hybrid Choice Model to Study Departure Time Choices. Submitted to *Transportation Research Board (TRB) 95th annual meeting*, Washington, USA, January 10-14, 2016.

The following article was also submitted during my PhD period, and deals with the general topic of the PhD, however, it is not presented as part of the thesis:

- External Paper 1: Thorhauge, M., Kaplan, S., Vuk, G., 2012. A Survey of Joint Activities and Travel of Household Members in the Greater Copenhagen Metropolitan Region. Published in *Selected Proceedings from the Annual Transport Conference at Aalborg University, ISSN 1903-1092*, Trafikforskningsgruppen, Aalborg University.
- External Paper 2: Walker, J. L., Wang, Y., Thorhauge, M., Ben-Akiva, M., 2014, D-Efficient or Deficient? A Robustness Analysis of SP Experimental Designs in a VOT Estimation Context. Proceedings of the *Transportation Research Board (TRB) 94th annual meeting*, Washington, USA, January 11-15, 2015

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I would also like to thank Senior Researcher Sonja Haustein for the constructive discussion related with the psychological theory and how it affects the problem of the departure time. Your contribution was vital for my research. I am also thankful to Professor Juan de Dios Ortúzar and Assistant Professor Julián Arellana for their valuable help on setting up the stated preference survey and the discussion on the departure time problem. Furthermore, I would like to thank Goran Vuk, Project Manager at the Danish Road Directorate, and Associate Professor Sigal Kaplan for including me in the ACTUM WP3 in the initial phase. It was a very rewarding collaboration, in which I learned a lot. Furthermore, thanks to Elisabetta – in her role as head of the PhD school at the department – for coordinating the PhD programme. Your effort is a tremendous asset for the department, and vital for all the PhD students, including me. Last, but not least I would like to thank my wonderful colleagues and fellow PhD students who created a wonderful and pleasant research environment, and given me some experiences I will never forget. A special thanks to Thomas, with whom I have spent many late nights in the office, and shared equally many late bike rides home from the University.

From September 2013 to February 2014 I visited University of California at Berkeley (UC Berkeley). It was a rewarding stay and it helped me to improve specific parts of the thesis. I would like to thank Associate Professor Joan L. Walker and everyone in her research group. A very special thanks to Joan for providing this opportunity and making me feel very welcome far from home. The feedback and discussions throughout the stay (and also during the remaining part of my PhD) have been invaluable for me. I would also like to thank Akshay Vij who kindly devoted time to discuss my research. Your input was very helpful, and fruitful for my dissertation. I would also like to thank all the people associated with the *Research Group* at UC Berkeley for our weekly discussions, and in addition a special thanks to Kara, Jenna, Timothy, Wei-Shiuen, and Andrew, who invited me to join their *Study Group*, for our weekly meetings and useful feedback. Also, many thanks to Yanqiao for our rewarding collaboration. Finally, I am thankful for some wonderful cookie hours, seminars, and a very fun Christmas get-together. Many students at the department and university showed great hospitality during my stay, not least the soccer teams. My five months in Berkeley passed by so quickly, and have given me an experience for life, something which I will always look back at with a smile on my face.

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SUMMARY

Copenhagen – like most other major cities – is facing problems with congestion, (especially) related to commuting in dense urban areas, in which the demand is condensed in peak-hours (Mahmassani, 2000; The Forum of Municipalities, 2008). A number of studies have shown that people are more likely to change their departure time rather than changing their transport mode to avoid congestion (Hendrickson and Planke, 1984; SACTRA, 1994; Kroes et al., 1996; Hess et al., 2007a). Hence, understanding the departure time choice from an individual perspective is important to develop policies aimed to address growing congestion issues.

A common approach to study departure time choices is the Scheduling Model originally formulated by Small (1982). Assuming that people have a specific preferred arrival time, the basic concept of the scheduling model is that individuals choose their departure time as a trade-off between travel time and a delay “penalty” resulting from being late or early. However, studying departure time choice is complicated as it is affected by additional factors. Firstly, it is related to a range of other trip-related decisions such as choice of mode, destination and trip purpose. Secondly, it is more generally related to the overall activity schedule of activities. Such an activity schedule is planned in coordination with household members as well as other social interactions, e.g. friends, colleagues, clients, etc. When considering activities within the activity schedule it is important to consider the level of flexibility (or lack of the same) as well. Flexibility is a complex issue affecting departure time in multiple dimensions. The most straightforward constraint when studying commuter trips is on the arrival time at the work place (e.g. due to individuals having fixed working hours) as the penalty of late arrival is very likely to be higher for individuals with constraints on arrival time. However, flexibility is not only a matter of fixed arrival time. Activities can be mandatory or discretionary (Yamamoto and Kitamura, 1999), performed alone or jointly with family and/or friends (Thorhauge et al., 2012), and restricted or non-restricted in terms of time and space (Bowman and Ben-Akiva, 2000). Depending on the type of activity, temporal, spatial and/or social constraints might play an important role in scheduling the activities and in choosing a specific departure time.

Parallel with the micro-economic theory, the psychological literature has evidenced that individuals’ behaviours are driven by underlying latent constructs, such as attitude, norms and perceptions. In the past decades, more attention has been given to incorporate and understand underlying psychological effects (such as attitude, norms, etc.) into discrete choice models (Koppelman and Lyon, 1981; Ortúzar and Hutt, 1984; McFadden, 1986). However, most studies usually focus only on a few latent constructs, often considering only attitudes (see e.g. Daly et al., 2012; Jensen et al., 2013; Paulssen et al., 2013; Kamargianni and Polydoropoulou, 2013; Kamargianni et al., 2014). None of these studies, nor any studies in the psychological literature, deal with the departure time problem. It is reasonable to believe that the departure time choice also can be substantially affected by individuals’ attitudes, norms and perception towards being on time (or towards reducing travel time and cost) other than by objective measure of times and costs. Arellana et al. (2012) are the only ones who consider these effects in the context of departure time, though they focus only on attitudes.

This thesis approaches the problem of the departure time choices for car commuters in the greater Copenhagen area under a more general framework that recognises that the choice of when to depart is affected by both micro-economic and psychological factors. Moreover, it is not an isolated decision, but rather a decision within a complex activity decision chain, where constraints imposed by one activity can

affect all other activities in the chain and in particular the preference for the departure time to work. Constraints can be objective (temporal, spatial and social) and directly affect individual departure time choice, but can also be perceived by the individuals as barriers towards participating in activities. Perceived constraints affect the departure time choice through the individual intention of being on time.

This PhD thesis also contributes to the departure time literature by discussing the problem of collecting appropriate data to analyse departure time choices. The travel time variation observed in revealed preference data is usually not large enough to be able to identify departure time preferences. For this reason, much recent research has used stated preferences data. Building stated preference designs is especially challenging for departure time studies because of the interdependence among attributes and the challenge of ensuring realism in the stated questions. Orthogonal designs are the predominant way of building stated experimental designs, while nearly none of the departure time studies have relied on efficient experimental designs. Koster and Tseng (2009) presented the first efficient design for departure time studies. Later, Arellana et al. (2012b) developed a pivoted efficient design including activity participation time (i.e. duration) at work. In order to create the design they had to sacrifice the traditional one-step process of creating efficient designs, thus relying on a two-step efficient design which reduces the efficiency. To the best of my knowledge, no researchers have used a fully efficient stated preference experimental design for the scheduling model.

Summarising, the contribution of this PhD thesis is as follows.

Firstly, it provides evidence of a fully efficient stated choice design for a departure time context. Using a pivot design (Rose et al., 2008) built around a reference trip (usually from the day before), the thesis shows that the efficient design performs well in cases where good prior knowledge about the parameters is available.

Secondly, it investigates the impact of accounting for a daily activity schedule and the corresponding constraints. It shows the importance of taking the daily activity schedule and their constraints into consideration. In particular, the thesis explores whether and to which extent the willingness to shift departure time to avoid congestion and willingness to pay for reducing travel time and travel delay to work is affected by the way information on flexibility at work is collected and by other trips/activities realised during the day and also whether they are constrained. The thesis also provides empirical evidences of the policy implication of not accounting for other activities and their constraints.

Thirdly, the thesis shows that the departure time choice can be partly explained by psychological factors, which have previously been neglected by nearly all studies within departure time. More importantly it shows that the underlying psychological processes are more complex than simply accounting for attitudes and perceptions which are typically used in other areas. The work in this PhD thesis accounts for the full Theory of Planned Behaviour (Ajzen, 1991), in which Intention act as a mediator between the underlying latent factors (attitude, norms, and perception). It was found that the psychological factors not only influenced the choice but also individual preferences.

RESUMÉ (DANISH)

Trængsel på vejene er et af de største problemer moderne storbyer står overfor. Trængsel er (især) relateret til pendling, hvor efterspørgslen overstiger vejnettets kapacitet (Mahmassani, 2000; The Forum of Municipalities, 2008). En række studier har vist, at folk er mere tilbøjelige til at ændre deres afgangstid i stedet for at ændre deres transportmiddel for at undgå trængsel (Hendrickson and Planke, 1984; SACTRA, 1994; Kroes et al., 1996; Hess et al., 2007a). Det er derfor vigtigt at forstå, hvad der påvirker folks valg af afrejsetidspunkt. Mere specifikt, i dette projekt undersøges (hvad der påvirker) valget af afrejsetidspunkt for pendlerture til arbejde i morgenmyldretiden.

En af de mest anvendte metoder til at studere valg af afrejsetider er Smalls (1982) *Scheduling Model* (SM), som antager at individer har et foretrukket mødetidspunkt på deres arbejdsplads. Det grundlæggende koncept i SM er, at individer vælger deres afrejsetidspunkt som en afvejning mellem rejsetid og en ”forsinkelsesstraf”. Denne forsinkelsesstraf er defineret ved forskellen mellem det foretrukne ankomsttidspunkt på arbejdspladsen og det faktiske ankomsttidspunkt, og er et udtryk for genen ved at ændre sit rejsetidspunkt. Typisk vil et afrejsetidspunkt, der ligger tæt på det foretrukne, resultere i en højere rejsetid (pga. trængslen i myldretiden), men have en lille forsinkelsesstraf. Valget af afrejsetidspunkt er i høj grad styret af, om de pågældende personer har faste eller fleksible mødetider. Det har ofte større konsekvenser for personer, der har faste arbejdstider, at komme for sent end for folk, der mere frit kan vælge deres mødetid.

Dog er folks valg af afrejsetidspunkt for pendlerture (ofte) en kompleks størrelse, som ikke kan betragtes som en isoleret beslutning, men bør ses i en større helhed. For eksempel kan begrænsninger i ankomsttidspunktet for en (anden) aktivitet i løbet af dagen kan betyde, at hele turkæden er fastlåst. Ydermere er andre aktiviteter i løbet af dagen ofte(re) koordineret i samspil med husstandens medlemmer, men også ift. øvrige sociale relationer, såsom venner, kolleger, kunder etc. Derfor er det vigtigt også at tage højde for disse aktiviteter samt for, om de er fleksible eller ej. Men fleksibilitet kan måles på mange måder, hvorfor man er nødt til – for at få den fulde forståelse – at tage højde for en række parametre, herunder om aktiviteterne er obligatoriske eller valgfrie (Yamamoto and Kitamura, 1999), udføres alene eller sammen med familie og/eller venner (Thorhauge et al., 2012), og er begrænset eller ikke-begrænset i tid og sted (Bowman and Ben-Akiva, 2000). Afhængig af aktiviteten kan en eller flere typer af begrænsninger gøre sig gældende. Det er vigtigt at bemærke, at sådanne restriktioner kan være afgørende for valget af afrejsetidspunkt for pendlerture, og i nogle tilfælde vigtigere end begrænsningerne på arbejdet. For eksempel kan det at følge et barn til skole være afgørende for, hvornår folk tager på arbejde, da barnet skal være i skole til skolestart, og dermed bliver det en styrende parameter for valget af afrejsetidspunkt for forældrene.

Typisk har valget af afrejsetidspunkt været studeret ud fra den mikroøkonomiske teori, som er velegnet til at modellere individers adfærd. Samtidig beskæftiger man sig inden for psykologiens verden også med at forklare de underliggende beslutningsprocesser for menneskers adfærd. Med tiden er der kommet større fokus på at integrere de psykologiske elementer i den mikroøkonomiske teori (Koppelman and Lyon, 1981; Ortúzar and Hutt, 1984; McFadden, 1986), og det er rimeligt at forvente, at valget af afrejsetidspunkt i høj grad også er påvirket af underliggende psykologiske elementer i forhold til at ankomme rettidigt. Dog fokuserer langt størstedelen af de tidligere studier (som har integreret psykologiske elementer med den mikroøkonomiske teori) kun på attitude (se fx. Daly et al., 2012; Jensen et al., 2013; Paulssen et al., 2013; Kamargianni and Polydoropoulou, 2013; Kamargianni et al., 2014), og ingen af disse studier har omhandlet valget af afrejsetidspunkt. Betydningen af psykologiske elementer for valget af afrejsetidspunkt er derfor et

stort set uudforsket område. Arellana et al. (2012) er det eneste eksempel, som tager højde for psykologiske processer i valg af afrejsetidspunkt, men undersøger også kun attitude. Det vides dog fra psykologien at den underliggende beslutningsproces er meget mere kompleks, og for at få en mere retvisende forståelse er det nødvendigt også at tage højde for andre psykologiske elementer såsom normer, opfattelse og intention.

Dette projekt bidrager også til den eksisterende forskning i forbindelse med dataindsamlingen. Størstedelen af (især nyere) studier vedrørende afrejsetidspunkter anvender SP-data (Stated Preference), da RP-data (Revealed Preference) sjældent indeholder nok variation i forhold til modelestimering. Ved SP-data defineres en række hypotetiske scenarier bestående af et valg mellem en række tilgængelige alternativer. Når man vil studere valget af afrejsetidspunkt, er denne proces særlig vanskelig, primært af to årsager: 1) attributterne i de hypotetiske scenarier er ikke uafhængige, men skal i stedet betragtes som en funktion af afrejsetidspunktet, samt 2) det er vanskeligt at sikre, at scenariet er realistisk for alle individer, da afrejsetidspunktet og længden (og dermed rejsetiden) af turen til arbejde kan variere meget fra person til person. Dette er vigtige problemstillinger, når der genereres hypotetiske valgsæt for valget af afrejsetidspunkter. Tidligere var *ortogonale designs* den primære metode til at generere hypotetiske valgsæt, men for nyligt har *effektive designs* fået større opmærksomhed, da de (alt andet lige) resulterer i mindre varians for de estimerede parametre. Blandt studier, der fokuserer på valg af afrejsetidspunkt, findes der kun to eksempler, der anvender et *effektivt design* (Koster and Tseng, 2009; Arellana et al., 2012b). For at gøre scenarierne mere realistiske for hvert enkelt respondent pivoterede Arellana et al. (2012b) deres design omkring en faktisk foretaget (reference)tur, men genererede dog designet gennem to trin, hvilket bryder med den underliggende teori. Så vidt vides, er der ingen, der har konstrueret et pivoteret og fuldt *effektivt design* med henblik på at studere valg af afrejsetidspunkter.

I dette projekt fokuseres der på valg af afrejsetidspunkter for pendlerture i København foretaget i bil. Dette gøres ved at definere en overordnet ramme, som omfatter en række vigtige elementer i beslutningsprocessen for valget af afrejsetidspunkt, herunder kompleksiteten i både eksterne begrænsninger samt interne psykologiske processer. Denne afhandling bidrager til den eksisterende forskning på følgende områder:

For det første er der genereret det første fuldt *effektive design*, som er pivoteret omkring en referencetur (Rose et al., 2008). Dette design blev genereret ved at indsamle alle informationer om folks aktiviteter og ture – normalt fra dagen før – og på baggrund af disse skræddersy et scenarie, der fremstod realistisk og i overensstemmelse med respondenternes eksisterende (pendler)tur. Dette gøres for, at folk lettere kan forholde sig til det valg, de skal foretage, samtidig med at begrænsningerne virker virkelighedstro. Desuden påvises det, at dette design fungerer godt i tilfælde, hvor god forhåndsviden om parametrene er tilgængelig.

For det andet undersøges konsekvenserne af folks fleksibilitet (eller mangel på samme), når de planlægger (af)rejsen til arbejde. Det er blevet påvist, at det er vigtigt at tage højde for dagens øvrige aktiviteter, og således ikke blot betragte pendlerturen som en isoleret rejse, da andre gøremål (og ikke mindst begrænsninger ifm. disse gøremål) i høj grad påvirker folks præferencer ift. mødetid på arbejde.

For det tredje viser afhandlingen, at valget af afgangstidspunkt bedre kan forklares, hvis der inddrages psykologiske elementer i modellen. I dette projekt er det påvist, at *Theory of Planned Behavior* (Ajzen, 1991) kan anvendes i samspil med den mikroøkonomiske teori til at forklare præferencer for afgangstidspunktet. Især blev det fundet, at den psykologisk del var velegnet til at beskrive de gener, folk oplever ved at komme for sent på arbejde. Dermed kan det konkluderes, at det vil være en simplificering at se bort fra psykologiske aspekter i beslutningsprocessen, som det typisk har været gjort førhen.

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1 INTRODUCTION

One of the strongest trends in the world of today is increasing urbanisation. One important impact of this is increasing congestion which increase travel time and reduces mobility significantly. The time and fuel wasted in traffic congestion also has direct financial and environmental consequences. The daily economical loss in relation to congestion in the Greater Copenhagen Area (GCA) has been amounted to a total of 6 billion DKK (approx. 800 million euros) (The Forum of Municipalities, 2008). In addition to the socio-economic consequences, congestion also impacts the environment, causing poor urban air quality and health risks (Levy et al., 2010). In recent years, the traffic volume within the GCA has increased by more than 10% annually (The Forum of Municipalities, 2008) and - like in other European capitals - it is expected to increase further due to urbanisation (Trængselskommissionen, 2013).

Congestion is (especially) related to commuting in dense urban areas, in which demand is condensed in peak-hours (Mahmassani, 2000). Thus, a shift in departure times could play a key role in reducing peak-hour congestion. A number of studies have shown that people are more likely to change their departure time to avoid congestion than to change their transport mode (Hendrickson and Planke, 1984; SACTRA, 1994; Kroes et al., 1996; Hess et al., 2007a). Despite this, departure time decisions have received relatively little attention compared to other areas of transport modelling, such as mode and route choices.

In the previous literature on departure time choices the main focus has been on the effect of changes in level-of-services (LOS) attributes. Table 1 provides an overview of the literature focusing on departure time choice. Papers are listed by year of publication and are classified by *time of reference* (i.e. whether departure time is modelled as a continuous or discrete choice), *type of data* (i.e. whether revealed preferences-RP- and/or stated preference-SP- data are used), *trip purposes* (distinguishing between work and non-work activities), *time period* (i.e. which time period of the day is considered). The last column indicates the type of model estimated. Some of the papers are only theoretical, while in some other cases information was not available. In these cases the lack of information is marked with a hyphen.

As we can see from the table, the vast majority of the papers used the discrete approach. The discretization of time naturally results in a loss of temporal resolution, and it often suffers from an arbitrary division of time into periods or points (Lemp et al., 2012). The continuous approach, which implies the use of hazard-based specifications (Wang, 1996; Bhat and Steed, 2002) does not have this flaw. However, the discrete approach has a number of advantages. A discretization of time usually goes hand in hand with the random utility maximization (RUM) theory, which is linked with the underlying micro-economic framework of behaviour and allows for computing consumer surplus (de Jong et al., 2007; Kockelman and Lemp, 2011). It can also be argued that travellers consider departure time in rounded intervals, commonly to the nearest 5 or 10 minutes (Coslett, 1977). In addition, current transport models often rely on Random Utility Maximisation (RUM) for other transport choices, which allow an easier integration.

Interestingly, almost all the papers using the discrete approach use the Scheduling Model (SM) originally formulated by Small (1982). The scheduling model is based on earlier work of Vickrey (1969) and Coslett (1977). Assuming that people have a specific preferred arrival time (PAT), the basic concept of the SM is that individuals choose their departure time as a trade-off between travel time (TT) and a delay “penalty” from rescheduling away from their PAT. If a traveller arrives at his or hers preferred arrival time then the penalty from the scheduling delay will be equal to zero. In such a situation the individual will not experience disutility from rescheduling. The SM is particularly suitable for our study of working trips, since individuals

often have a well-defined preferred arrival time at work (Day et al., 2010), and hence trade travel time and scheduling delay in order to avoid or minimize congestion. The SM was extended a couple of years later to first include travel cost (Small, 1987), which is crucial to compute values of travel time, and then later to include a discrete lateness penalty to specifically capture the impact of late arrive (Noland and Small, 1995) and travel time (un)reliability (Noland and Small, 1995; Small et al., 1995; 2000; Noland et al., 1998; Lam and Small, 2001). The latter accounts for uncertainty about the actual travel time along a journey (i.e. the unexpected delay). Travel time (un)reliability is also referred to in the literature as travel time variability (TTV), and it is important because people who are risk-averse might re-think their departure time choice in the presence of travel time variability (Fosgerau et al., 2008). The Scheduling Model will be discussed further in section 3.2.

Studies	Time of reference	Type of data	Trip purpose	Time period	Model type used in time of day
Vickrey, 1969	Continuous	-	(W)	(A.M. commute)	Deterministic
Coslett, 1977	Discrete	RP	W	A.M. commute	MNL
Abkowitz, 1981	Discrete	RP	W	A.M. commute	MNL
McCafferty and Hall, 1982	Discrete	RP	W	P.M. commute	MNL
Small, 1982	Discrete	RP	W	A.M. commute	MNL
Hendrickson and Planke, 1984	Discrete	RP	W	A.M. commute	MNL
Small, 1987	Discrete	RP	W	A.M. commute	MNL, NL and OGEV
Mannering, 1989	# of changes per month	RP	W	A.M. commute	Poisson regression
Arnott et al., 1990	Continuous	-	W	A.M. commute	Deterministic
Chin, 1990	Discrete	RP	W	A.M. commute	MNL (NL did not converge)
Mannering et al., 1990	Continuous	RP	W	A.M. commute	MNL, continuous Weibull survival function
Chu, 1993	Discrete	RP	W	A.M. commute	NL
Hamed and Mannering, 1993	Continuous	RP	N	Post-work	Continuous Weibull survival function
Levinson and Kumar, 1993	Discrete	RP	W & N	P.M. commute	MNL
Arnott et al., 1994	Continuous	-	W	A.M. commute	Deterministic
Polak and Jones, 1994	Discrete	SP	W & N	A.M. & P.M. commute	NL
Chin et al., 1995	Discrete	RP	W	A.M. commute	Incremental logit (MNL)
Khattak et al., 1995	Discrete	SP	W	A.M. commute	Ordered probit
Noland and Small, 1995	Discrete	-	W	A.M. commute	Use parameters from previous study
Small et al., 1995	Discrete	SP	W	A.M. commute	MNL
Koskenoja, 1996	Discrete	SP	W	A.M. commute	Binary logit
Wang, 1996	Continuous	RP	W & N	Full day	Weibull and log-logistic hazard
De Palma et al., 1997	Discrete	SP	W	A.M. commute	OLS & Tobit
Hunt and Patterson, 1997	Discrete	SP	N	Hypothetical	Exploded logit
Bhat, 1998a	Discrete	RP	N	Full day	MNL-OGEV
Bhat, 1998b	Discrete	RP	N	Full day	MMNL, MNL
Bianchi et al., 1998	Discrete	SP	W	A.M. & P.M. commute	OP
Noland et al., 1998	Discrete	SP	W	A.M. commute	Binary logit
Steed and Bhat, 2000a	Discrete	RP	N	Full day	MNL, OGEV
Steed and Bhat, 2000b	Discrete	RP	N	Full day	MNL, OGEV
Bhat and Steed, 2002	Continuous	RP	N	Full day	Continuous-time hazard duration model
Lam and Small, 2001	Discrete	RP	W	A.M. Commute	MNL, NL
de Jong et al., 2003	Discrete	SP	W & N	A.M. & P.M. commute	EClogit, MNL
Ashiru et al., 2004	Continuous	Hypothetical	W & H	Home-work-home tour	Numerical maximization (Hooke and Jeeves pattern search algorithm)

Studies	Time of reference	Type of data	Trip purpose	Time period	Model type used in time of day
Ettema et al., 2004a	Discrete	SP	W & H	Full day	MNL
Ettema et al., 2004b	Discrete	SP	W	A.M. commute	MNL
Hess et al., 2005	Discrete	SP	W	A.M. & P.M. commute	MNL
Tseng et al., 2005	Discrete	SP	W	A.M. commute	MNL
Hollander, 2006	Discrete	SP	W	A.M. commute	MNL
Börjesson, 2007	Discrete	RP/SP	W	A.M. commute	ML
Hess et al., 2007a	Discrete	SP	W & N	Full day	MNL, NL, ML
Hess et al., 2007b	Discrete	SP	W & N	A.M. & P.M. commute	MMNL EC
Holyoak, 2007	Discrete	RP	W	A.M. & P.M. commute	ML
Börjesson, 2008	Discrete	RP/SP	W	A.M. commute	ML
Tseng and Verhoef, 2008	Discrete	SP	W	A.M. commute	MNL, ML
Bajwa et al., 2008	Discrete	SP	W	A.M. commute	ML, NL
Börjesson, 2009	Discrete	RP/SP	W	A.M. commute	ML
Habib et al., 2009	Continuous	RP	W	A.M. commute	Continuous time hazard model
Koster and Tseng, 2009	Discrete	SP (simulated)	-	-	Binary logit
Fosgerau and Karlström, 2010	Continuous	RP	(W)	A.M. commute	Nonparametric kernel regression
Lemp and Kockelman, 2010	Continuous	RP	W	A.M. commute	Continuous Logit
Lemp et al., 2010	Continuous	RP	W	A.M. commute	Continuous cross-nested logit model
Arellana, 2011	Discrete	SP	W	A.M. commute	MNL
Arellana et al., 2012a	Discrete	SP	W	A.M. & P.M. commute	MNL, MMNL
Koster et al., 2011	Discrete	SP	W & N	Airport transit	Binary panel mixed logit model
Tseng et al., 2011	Discrete	RP/SP	W	A.M. commute	MNL, ML
Arellana, 2012	Discrete	SP	W	A.M. & P.M. commute	MNL, ML, HCM
Arellana et al., 2012b	Discrete	SP	W	A.M. & P.M. commute	MNL
Borjesson et al., 2012	Discrete	SP	W	A.M. & P.M. commute	Binary logit models.
Koster and Verhoef, 2012	Discrete	RP/SP	W	A.M. commute	Rank dependent model
Wang, 2012	Discrete	SP	W	A.M. & P.M. commute	Binary logit models.
Lemp et al., 2012	Continuous	RP	W & H	Full day	Multinomial Probit Model
Lizana et al., 2013	Discrete	SP	W	A.M. commute	MNL, ECL
Kristoffersson, 2013	Discrete	RP/SP	W	A.M. commute	ML

Table 1: Overview of departure time studies (W: Work, N: Non-work, H: Home)

The vast majority of the studies focus on work trips and in some cases work tours. Only very few cases explicitly consider non-work trips. This naturally implies that many studies also focus on the peak hours, especially the morning peak hours. The reason for this is that morning peak hours are normally more condensed; hence the incentive (i.e. the potential gain) to re-schedule the departure time is higher. Departure time has been studied using both Revealed Preference (RP) and Stated Preference (SP) data. However, RP data are used mainly in the early studies (before 1995), while in more recent studies SP data are used more frequently. Very few studies use joint RP/SP data and all are recent studies (after 2007). The advantages of using RP or SP will be discussed later in Section 4. Finally, many studies rely on the simple Multinomial Logit (MNL) model, albeit the Mixed Logit (ML) model has gained ground in particular to account for panel effect in the SP data. The work of Arellana (2012) remains the only one where a Hybrid Choice Model (HCM) is used to account for attitudinal effects.

One important aspect when studying departure time is individuals' flexibility (or lack of it). Flexibility is a complex issue that (potentially) affects departure time in multiple dimensions. The most straightforward constraint when studying commuter trips is to account for arrival time constraints at the work place. In the thesis I will explore the working hypothesis that the penalty of late arrival is higher for individuals with arrival time constraints. However, trip timing can also be affected by other activities in the trip chain to work or other activities during the day. Transport models have already acknowledged this fact by extending the model framework to consider tours rather than single trips to better describe dependencies within trip chains, and as a consequence model individuals' trips as tours consisting of both outbound and homebound trips rather than single isolated trips (Bowman and Ben-Akiva, 2000). More recently, Activity Based models (AB-models) have gained popularity as they overcome the restrictions of traditional trip- and tour-based models. The core belief in AB-models is that travel demand emerges from a fundamental need for individuals to engage in different types of activities, (see e.g. Jones, 1977). This is achieved by explicitly modelling individual's daily activity schedule (Ben-Akiva et al., 1996; Ben-Akiva and Bowman, 1998), which allows implicitly capturing interdependencies among activities in the daily schedule.

Even though trip timing is important for the resource allocation and the departure time, other types of constraints can potentially play an important role. More specifically, activities can be mandatory or discretionary (Yamamoto and Kitamura, 1999), performed alone or jointly with family and/or friends (Chandrasekharan and Goulias, 1999; Yarlagaadda and Srinivasan, 2008; Thorhauge et al., 2012), and restricted or non-restricted in terms of time and space (Bowman and Ben-Akiva, 2000). In order to fully understand how constraints are combined across activities in the activity schedule one must consider the multiple dimensions of constraints, including temporal, spatial and social dimensions.

In recent years, departure time studies have incorporated scheduling constraints by including tour chains consisting of both the trip from home to work and the trip back home from work, hence implicitly including the activity participation time of the main activity, i.e. working time (de Jong et al., 2003; Ettema et al., 2004a; Hess et al., 2007a; Hess et al., 2007b; Arellana et al., 2012a). However, these studies do not include complex trip chains, and hence also disregard trip chains with intermediate stop(s) on the trip to and/or from work, or even activities performed during sub-tours while at work. Similarly, other tours conducted before or (more likely) in the evening after the main (work-)tour have not been included in current departure time models either. In addition, previous studies have acknowledged the fact that scheduling constraints are not equal for all individuals. To account for this Hendrickson and Planke (1984) defined zero scheduling delay for individuals with flexible working hours, while a more common approach has been to capture differences in scheduling preferences by including general questions regarding whether respondents had fixed or flexible working hours or if they have any restrictions with respect to late arrival (Small, 1982; Mannering, 1989; Chu, 1993; Small et al., 1995; de Jong et al., 2003; Hess et al., 2007a; 2007b; Börjesson, 2007; 2008; 2009; Arellana et al., 2012b). Although these two ways to measure flexibility are used for the same purpose in departure time models, they are not comprehensive enough to reveal the true constraints in the choice of departure time, and they might convey different type of information. Moreover, as discussed in the activity-based literature, departure time to work can also be affected by other activities carried out during the day, and by constraints (spatial, time and coupling) on these other activities. All these effects should be properly measured and accounted for. Understanding and quantifying these effects is of particular relevance when assessing transport policies to avoid overestimating the demand elasticity in response to crucial intervention such the implementation of congestion pricing schemes.

The theory discussed so far assumes that scheduling choice depends only on the objective characteristics of the trip (and activity), hence times, cost and delays, and whether or not the arrival time is flexible. However, as shown in many other fields, it is reasonable to believe that the departure time choice can also be affected by underlying latent constructs, such as attitude, norms and perceptions. In the field of psychology, a number of theories explaining behaviour have been proposed, such as the *Norm Activation Model* (Schwartz, 1977; Schwartz and Howard, 1981), the *Theory of Interpersonal Behaviour* (Triandis, 1977), and the *Theory of Planned Behaviour* (Ajzen, 1991). The Theory of Planned Behaviour (TPB) formulated originally by Ajzen (1991) as a generalization of the *Theory of Reasoned Action* (TRA, Ajzen and Fishbein, 1980), is one of the most well-established psychological theories applied in the context of travel behaviour. In the original TPB, *Intention* (to behave in a given way) is the most important construct in terms of behaviour, and it is explained by underlying processes such as *Attitude*, *Subjective (Personal and Social) Norm (SN)*, and *Perceived Behavioural Control (PBC)*. *Attitude* measures individuals' attitudinal standpoint with respect to the behaviour. *Subjective norm* is defined as the perceived personal and social pressure towards behaving in a certain way, while *Perceived Behavioural Control* measures individuals' perceptions regarding their ability to perform a specific behaviour.

The effect of constraints also plays a central role in the psychological theory, though more in terms of perceived constraints. According to Ajzen and Driver (1992) *Perceived Behavioural Control* are influenced by perceived barriers towards participating in activities. Furthermore, Ajzen and Driver (1992) also directly compared Perceived Behavioural Control with the constraints often used in the literature on participation in leisure activities. Two individuals may have different perceptions towards a constraint – and equally important – the consequences of violating that constraint. Thus the perception of constraint is very important (Alexandris et al., 2007). Another link between constraints and the psychological elements in the TPB was suggested by Dawson et al. (2001). They hypothesised that constraints also influence attitude and social norms. However, Alexandris and Stodolska (2004) showed that the dominant link (in recreational sport participation) was formed by the link between the constraints and PBC and to a lesser extent between constraints and attitude and social norms. Alexandris et al. (2007) arrived at similar findings, albeit they found constraints to have no influence on the social norms.

In the past decades, more attention has been given to incorporate and understand underlying psychological effects (such as attitude, norms, etc.) into discrete choice models (Koppelman and Lyon, 1981; Ortúzar and Hutt, 1984; McFadden, 1986). In the transportation literature, starting with the work of Walker (2001), several studies have incorporated latent variables to better explain the discrete choice by capturing psychological latent constructs. However, most studies usually focus only on a limited number of latent constructs, and often consider only attitudes (see e.g. Arellana, 2012; Daly et al., 2012; Jensen et al., 2013; Paulssen et al., 2013; Kamargianni and Polydoropoulou, 2013; Kamargianni et al., 2014). Studies which also consider perception include Bahamonde-Birke et al. (2014) and Kamargianni and Polydoropoulou (2014). Furthermore, very few studies apply the correct hierarchical structure of the latent variables, although none account for the TPB. Finally, none of these studies, nor any studies in the psychological literature, deal with the departure time problem. Arellana et al. (2012b) are the only ones who measure individuals' attitude in the context of departure time. However, like the majority of the studies they only consider attitudes.

Last but not least, a major problem in studying departure time is represented by the availability of appropriate data. Revealed preference data usually suffer from lack of variation in time and cost attributes. For this reason most studies used stated preference data. However, the construction of SP designs is challenging for departure time studies because of *i*) interdependence among attributes, and *ii*) the need to obtaining realism in the choice task is tied specifically to each respondents.

Previously, orthogonal designs were the predominant way of building stated experimental designs, while nearly none of the departure time studies have relied on efficient experimental designs. Koster and Tseng (2009) presented the first efficient design for departure time studies. Later, Arellana et al. (2012b) developed a pivoted efficient design including activity participation time at work, albeit they, in order to create the design, had to sacrifice the traditional one-step process of creating efficient designs, thus relying on a two-step efficient design which reduces the efficiency. However, to the best of my knowledge, no one construct a fully efficient stated preference experimental design for the scheduling model pivoted around a reference alternative.

The purpose of this PhD thesis is to understand what influences the choice of departure time, by accounting for flexibility constraints and underlying psychological factors. As explained above, it is expected that accounting for such effects will be a key determinant in understanding and explaining the departure time behaviour. To achieve this goal, specific data with a great level of details are needed, and one purpose of this thesis is to deal with the problem of data collection in departure time choice contexts. The specific contribution of this PhD thesis can be summarised as to:

- 1) Explore the use of efficient stated choice designs for studying departure time modelling
- 2) Explore the information conveyed by the typical ways of measuring flexibility for work trips
- 3) Specifically account for the constraints that other activities realised during the day have on the choice of work departure time
- 4) Explore the broader spectrum of psychological effects that influence departure time choices and in particular the intention to behave in a given way with respect to the observed behaviour
- 5) Providing empirical evidence of the effects listed above in predicting the demand for departure time.

This thesis intends to discuss an overall framework for the departure time and to present the background theory. The specific methodologies, approaches and results are described in the papers. Thus, chapter 2 reports a discussion of the overall conceptual framework of the departure time decision; chapter 3 describes the overall model framework of discrete choice models, and in particular the hybrid choice models. In chapter 4, I discuss the problem of collecting data to study the influence of flexibility constraints and psychological factors in departure time problems. In chapter 5, I summarize the objectives, contribution and main results of each paper, while chapter 6 concludes the dissertation.

2 CONCEPTUAL FRAMEWORK OF DEPARTURE TIME CHOICES

As discussed in the introduction, departure time choice is affected by multiple factors. As a result, the choice cannot be seen as an individual isolated decision, but should be considered in a broader perspective. More specifically, departure time decisions are made in accordance with the overall activity schedule. The activity schedules are planned in accordance with individual preferences and restrictions. Individual preferences are formed by how individuals assess changes in level-of-service attributes (such as travel time and delay) but also potentially by underlying psychological elements (such as attitude and perception). Restriction can be formed by the activity, by social or work-related obligations or by intra-household constraints. It follows that these may represent temporal, spatial, and social dimensions. Restrictions for one activity can be transferred to other activities and potentially “show-stop” entire activity chains. Furthermore, resource allocation to certain activities might be performed with a weekly or monthly “rhythm”, thus considering single day activity schedules, might not allow capturing the full nature of some elements, such as intra-household coordination of escorting trips.

Ultimately, this makes the case for a rather complicated decision process of inter-linked spatial, temporal and social patterns and involves decisions about not just the departure time itself, but also the sequence, destination, duration and social interaction(s) across the activity schedule. Whether and to which extent individuals are able or willing to adjust their departure time depends on the nature of these scheduling processes.

Figure 1 illustrates the conceptual framework relating to departure time choices and how the various elements concur to shape the individual decision process. The framework is not restricted to the departure time choice, though I had built it with this specific problem in mind.

In a traditional micro-economic framework, such as the scheduling model, models are estimated by defining a set of observable attributes (level of services, socio-economic characteristics and objective constraints), while observing the behavioural output, e.g. the departure time choice for a specific activity (mainly work) and for all the activities realised before and after work. The squared boxes in Figure 1 indicate that the elements are measurable, such as attributes (e.g. cost, travel time, etc.), objective constraints (time, money, other activities, other people, availability, etc.), and socio-demographics (e.g. age, gender, education). Objective constraints reduce the utility of a given alternative (and it can also make the alternative unavailable). Constraints in a specific activity/trip can be due to limitations in any other activity/trip realised during the day (sometimes during the week), but it can also be limitations due to interaction with other people (mainly family and friends).

In the traditional microeconomic framework individual preferences are assumed to be “primitive, consistent, and immutable” (*preference rationality*). Furthermore, consumers behave *as if* they possess the formal tools with which to calculate the optimum adequately (*perception-rationality*), and the cognitive process is simply preference maximization, given market constraints (*process-rationality*) (McFadden, 1999). In Figure 1, this traditional process is illustrated by boxes and arrows in bold. Individuals’ preferences come from the “black box” (using the definition given by McFadden, 1986), but in the traditional microeconomic theory, what is inside the black box is not of relevance.

Psychologists’ prime objective has been to understand what happens inside that black box: the nature of these decision elements, how they are established and modified by experience, and how they determine values. In Figure 1, this process is illustrated by the boxes with a grey shadow.

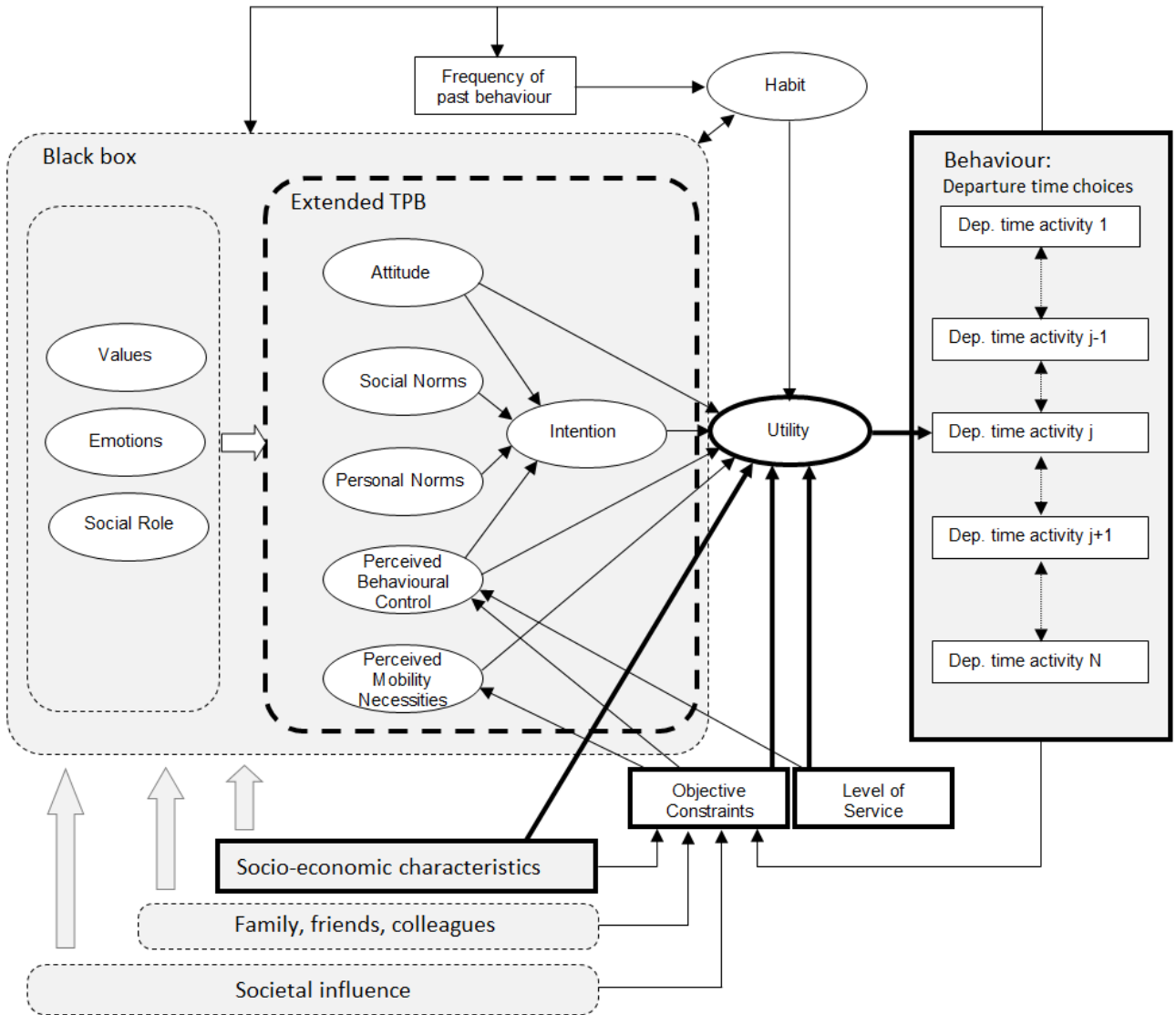


Figure 1: Conceptual framework for departure time decisions.

When representing the psychological aspect, I mainly follow the TPB theory, but I extended it to account for later developments. According to the psychological theory the observable behaviour is directly determined by the intention to behave in a certain way. Individual preferences are the overall process in the black box that shapes the intention to perform certain behaviour. Habit and objective constraints might prevent an intended behaviour to be actually performed. Socio-economic characteristics might also affect the way an intention turns into an observable behaviour, though in the psychological theory, socio-economic characteristics are implicit in the process depicted inside the black box. Intentions are determined by attitude, social and personal norms and perceptions about needs and behaviour control. As defined in the introduction, *Attitude* measures individuals' attitudinal standpoint with respect to the behaviour. *Subjective norm* is defined as the perceived personal and social pressure towards behaving in a certain way, while *Perceived Behavioural Control* measures individuals' perceptions regarding their ability to perform a behaviour.

Perceived Mobility Necessity is defined as people's perception of mobility as a consequence of their personal living circumstances. Overall, all these effects are influenced by a higher level of effects represented by value, emotions and social roles. Values represent fundamental beliefs considered trivial to all individual (Schwartz et al., 2001; Paulssen et al., 2013). Emotions help explaining why the same individual makes different choices all other things being equal (e.g. Scherer, 2005; McFadden, 2013) and in particular affect for example the individuals' perception of being able to undertake a given behaviour. Social role refers to the set of norms that apply within each social group. Typically each individual has been assigned a role (explicitly or implicitly), and thus individuals tend to navigate within the boundaries of those rules and roles, while at the same time trying to be in line with their own personal norms (e.g. Cialdini, 2007). The psychological theory also recognises that, as individuals interact with other individuals on a daily basis – that being friends, family, colleagues, relatives, or plain strangers – they make decisions in accordance with unwritten rules in the social circles they interact with.

As discussed in the introduction, constraints are often not only objective constraints, but perceived barriers towards participating in activities. Crawford and Godbey (1987) divided constraints into three types: intrapersonal, interpersonal, and structural constraints. Intrapersonal constraints are mainly related to individual characteristics (e.g. lack of skills) and psychological items, (e.g. perceived constraints). Interpersonal constraints are related to social constraints in relation to other individuals, while structural constraints are external such as they have been traditionally conceptualized (e.g. time or money constraints). Studies have found the intrapersonal constraints to be the most powerful in determining participation in a given (leisure) activity (Alexandris and Carroll, 1997; Alexandris et al., 2002; 2007).

The major problem when dealing with constraints is disentangling the influences among psychological elements and barriers. More specifically, is it the perception that shapes the level of restrictions formed by activity constraints, or is it the activity constraints that influence the individual perception towards being able to undertake an activity? On one hand, one could argue that two individuals attending the same activity (and thus could be assumed to face the same type of activity constraints), may not necessarily make the same choice, e.g. arrive at the same time. On the other hand, one could argue that the perception towards a given behaviour is likely to be influenced by the type and level of constraint which apply for a given activity. Thus, the answer might not be straightforward, as the behavioural process might in fact be influenced by some level of circular feedback mechanism, in which constraints affect attitudes and perception and vice versa.

In this thesis I try to approach the problem of the departure time choice in an integrate way, as illustrated in Figure 1. However, since the full phenomenon is rather complex, in this thesis I will not focus on the effect of habit, and the higher level of psychological effects, mainly values and emotions. Also, I will not specifically measure the societal effects.

3 MATHEMATICAL MODEL OF DEPARTURE TIME CHOICES

The mathematical model used to test the framework described in the previous section is based on the structure of hybrid choice models to combine the full structure of the theory of planned behaviour with the microeconomic scheduling theory.

In this chapter I will first briefly describe the theoretical foundation of discrete choice models and its specification under the scheduling approach. Then I will describe the hybrid choice specification that allows to incorporate the TPB in the SM, and to test the framework described in the previous section.

3.1 MODELLING CHOICES: THEORETICAL BACKGROUND

Discrete choice models typically rely on a compensatory decision rule¹, which implies that the attractiveness of an alternative is reducible to a scalar, and individuals make an evaluation of the available alternatives and select the alternative which yields the highest level of utility (utility maximisation). Modellers rely on random utility maximization (RUM) and the utility is considered a random variable (Ben-Akiva and Lerman, 1985). This is done for a number of reasons. Firstly researchers acknowledge that it is impossible to measure all explanatory variables describing the choice. In addition, it is not realistic to assume that all people behave completely rationally; hence some people might choose irrationally in the sense that they choose an alternative which (according to the deterministic model) does not yield the highest utility.

In the basic version of the discrete choice model, to make the model operation, the utility is split into two parts², a systematic (i.e. deterministic) part, which captures the measurable and observable utility, and a random (i.e. stochastic) part, which captures unobserved utility. Denote the systematic utility V , and the random element ε . Thus, the overall utility U of alternative i for individual n and choice situation t is typically written as:

$$U_{int} = \beta_{z,i}z_i + \beta_{x,i}x_{int} + \varepsilon_{int} \quad (1)$$

where x_i is a vector of characteristics of the alternative and of the individuals, as well as non-linear transformation of them. z_i is a vector of unobserved attributes (namely the alternative specific constants, ASC) while, $\beta_{z,i}$ and $\beta_{x,i}$ are the vectors of corresponding parameters, describing the influence of these variables on the utility.

Since the overall utility U is a random variable, the choice is given by the probability that the utility of the chosen alternative is greater than the utility of any other alternative in the choice set:

¹ In this thesis I will refer only to compensatory decision rules, but discrete choice models have been extended to account for not compensatory decision rules, like: **Dominance**: if one alternative is better for at least one attribute and no worse for all the others attributes. **Satisfaction**: if individuals associate to each attribute a minimum level, which represents the “level of aspiration” that must be satisfied and eliminated the alternative from the choice set if at least one attribute does not satisfy the criterion. **Lexicographic**: if individuals have rank ordered the attributes by level of importance and chooses the alternative which is most attractive for the most important attribute.

² Later we will deviate slightly from this rigid definition.

$$P_{int} = Pr(U_{int} \geq U_{jnt}, \forall i \in C_n, j \neq i) \quad (2)$$

If we denote $f(\boldsymbol{\varepsilon}) = f(\varepsilon_1, \dots, \varepsilon_N)$ the density function of the error term in equation (1) the probability of choosing alternative i can then be computed as:

$$P_{int} = \int_{R_N} f(\boldsymbol{\varepsilon}) d\boldsymbol{\varepsilon} \quad (3)$$

$$R_N = \left\{ \begin{array}{l} \varepsilon_{jnt} < \varepsilon_{int} + V_{int} - V_{jnt}, \forall j \in C_{nt}, j \neq i \\ V_{int} + \varepsilon_{int} \geq 0 \end{array} \right. \quad (4)$$

Assuming the error terms to be independently and identically distributed (iid), extreme value type 1 (EV1), the typical closed form of the Multinomial Logit (MNL) model, is obtained:

$$P_{int} = \frac{e^{\lambda V_{int}}}{\sum_{j \in C_n} e^{\lambda V_{jnt}}} \quad (5)$$

where λ is the scale factor which in practice is normalized to 1. Normalization also implies that only N-1 alternative specific constants (ASC) can be specified, thus one is normalized to 0. As well known, the iid assumption is quite restrictive and the MNL formulation has been extended in several ways. One of the most common extensions is the Mixed Multinomial Logit (MMNL) model – or Mixed Logit (ML) model – which is a highly flexible model that can approximate any random utility mode (McFadden and Train, 2000). More specifically, the ML is characterised by an error term with at least two components: one for obtaining the logit probability with the usual Extreme Value type 1 (EV1) distribution, and a second term that accounts for different components of unobserved heterogeneity, the distribution of which can be freely chosen by the modeller (Train, 2009). The most general utility for the ML model can be written as:

$$U_{int} = \lambda (\boldsymbol{\beta}_{z,nit} \mathbf{z}_i + \boldsymbol{\beta}_{x,int} \mathbf{x}_{int}) + \varepsilon_{int} \quad (6)$$

where all the terms have the same meaning as defined in equation (1) but $\boldsymbol{\beta}_{z,nit}$ and $\boldsymbol{\beta}_{x,nit}$ are vectors of parameters randomly distributed with means $\boldsymbol{\beta}_{z,i}$ and $\boldsymbol{\beta}_{x,i}$ and variance-covariance matrix Ω_z and Ω_x . These parameters allow accounting for random heterogeneity in the preference for specific attributes, in the preference for specific alternatives, correlation among alternatives and correlation among multiple observations from the same individuals (e.g. the typical choice tasks in the stated preference data). Let V_{int} be the utility in equation (6) excluding the iid random term ε_{int} , the probability of alternative i for individual n is then given by:

$$P_{in} = \int_{\boldsymbol{\beta}} \prod_{t=1}^T \left(\frac{e^{V_{int}(\boldsymbol{\beta})}}{\sum_j e^{V_{jnt}(\boldsymbol{\beta})}} \right) f(\boldsymbol{\beta}|\Omega) d\boldsymbol{\beta} \quad (7)$$

3.2 THE SCHEDULING MODEL

The scheduling model assumes that travellers are faced with a discrete number of alternative departure times and they make a trade-off between travel time and cost, and the penalty for rescheduling, i.e. being early or late. The utility in equation (6) for the scheduling problem takes then the following general specification:

$$U_{int} = \beta_{TT,int}E(TT_{int}) + \beta_{TC,int}TC_{int} + \beta_{SDE,int}E(SDE_{int}) + \beta_{SDL,int}E(SDL_{int}) + \beta_{DL,int}DL_{int} + \beta_{z,int}z_i + \varepsilon_{int} \quad (8)$$

where TT is the total travel time from origin to destination, which in principle is a function of the departure time (DT). Similarly, TC is the travel cost with respect to DT , while $E(SDE)$ and $E(SDL)$ are the expected scheduling delays, i.e. the expected cost of arriving early or late, respectively. DL is a dummy variable that accounts for the discrete lateness penalty.

Based on the literature, travel time variability has been included in two ways: expected travel time and mean variance. Both have strengths and weaknesses, but they differ in the underlying assumptions (Fosgerau et al., 2008). The mean-variance approach is intended to capture the nuisances of travel time variation independent of late (or early) arrival. On the other hand, the expected travel time approach (also referred to as scheduling approach) assumes that travel time variations influence utility implicitly through intention, hence uncertainty in travel time will cause individuals to be late (or early) on average. Some authors (Noland et al., 1998; Small et al., 2000) have found the expected travel time approach to be superior. In this study I follow this later approach and I included travel time variability as the expected travel time, $E(TT)$. Given a series of $s = 1, \dots, I$ different travel times for each alternative of different i and each choice situation of different t , the expected travel time is the sum of the travel time weighted by the probability p_s that each travel time occurs:

$$E(TT_{int}) = \sum_{s=1}^S p_s(TT) \cdot TT_{ints} \quad (9)$$

And the expected scheduling delays have the following expressions:

$$E(SDE_{int}) = \sum_{s=1}^S p_s \cdot SDE_{ints} = \max(-DT_{int} + E(TT_{int}) - PAT_n; 0) \quad (10)$$

$$E(SDL_{int}) = \sum_{s=1}^S p_s \cdot SDL_{ints} = \max(0; DT_{int} + E(TT_{int}) - PAT_n) \quad (11)$$

where $\sum_{s=1}^S p_s = 1$.

Conceptually, the Schedule Delay (SD) is defined as the difference between the Preferred Arrival Time (PAT) and the actual Arrival Time (AT) of alternative i for individual n and choice task t . Since AT must be equal to the departure time plus the total travel time, the SD for alternative i , individual n and choice task t is defined as:

$$SD_{int} = AT_{int} - PAT_n = DT_{int} + E(TT_{int}) - PAT_n \quad (12)$$

If a traveller arrives at his or her preferred arrival time, then SDE and SDL will be equal to zero. This yields that the individual will not experience disutility from rescheduling. Figure 2 provides an easy visualization of the disutility of the scheduling model.

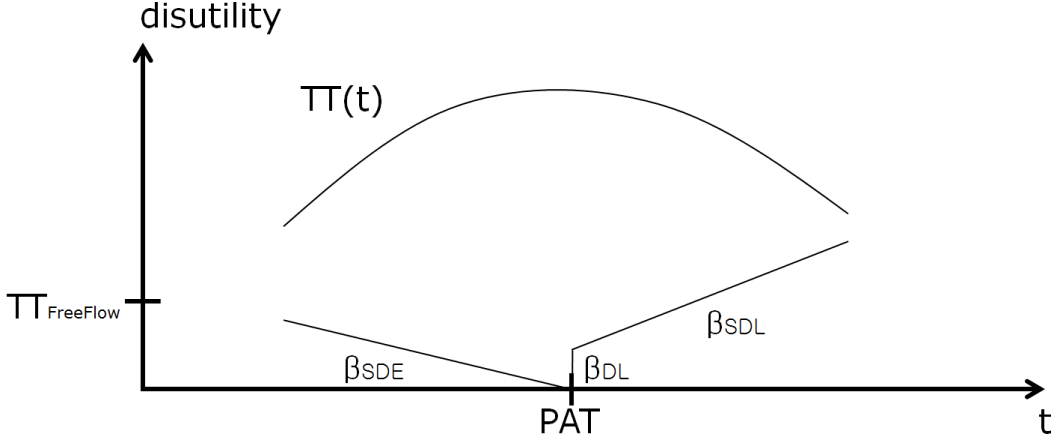


Figure 2: Visualization of the disutility of the scheduling model

It is important to mention that the coefficients β in equation (8) are allowed to vary among alternatives, individuals and choice tasks. Let x be the generic level-of-service (LoS) attribute (time, cost, delay and so on), the coefficient $\beta_{x,int}$ takes the following general form:

$$\beta_{x,int} = \beta_{x,i} + \beta_{x,SE} \mathbf{SE}_n + \beta_{x,FC} \mathbf{FC}_n + \gamma_{x,int} \quad (13)$$

where \mathbf{SE}_n is a vector of socio-economic variables, \mathbf{FC}_n is a vector of dummy variables to account for the effect of daily activities and flexibility constraints (i.e. the effect of objective constraints in the utility), and $\gamma_{x,int}$ is a random term distributed with mean zero and variance-covariance matrix Ω_x . The model then in its general form allows the marginal utility of all the LoS attributes to depend on the individual socio-economic characteristics, the activities performed during the day and the flexibility constraints and random heterogeneity.

3.3 JOINT MODEL: INTEGRATING TPB AND SM

Following the theory of hybrid choice models, the utility specification in equation (6) needs to be extended to incorporate the psychological effects into the discrete scheduling model. For simplicity of notation, let us use the compact form as in equation (6), the utility specification then takes the following form:

$$U_{int} = (\beta_{z,int} \mathbf{z}_i + \beta_{x,int} \mathbf{x}_{int})(1 + \beta_{\mathbf{X}^*,int} \mathbf{X}_n^*) + \varepsilon_{int} \quad (14)$$

where \mathbf{X}_n^* is vector of M latent variables for the individual n . The latent variables can affect the preference for specific characteristics and/or for a specific departure time alternative. Each element in the vector is

defined by a structural equation, linking the latent effect to a set of observed (socio-demographics) variables likely to influence the latent variable, and, in the case of hierarchical latent structures (like in the case of the TPB), to other latent variables which we denote $\mathbf{X}_{n'}^{**}$ ($n' \neq m$). Thus, we define the *structural* equation for latent variable m as:

$$X_{m,n}^* = \theta_m + \lambda_m \cdot \mathbf{S}_n + \boldsymbol{\partial}_m \cdot \mathbf{FC}_n + \boldsymbol{\gamma}_m \cdot \mathbf{X}_{m,n}^{**} + \omega_{m,n} \quad (15)$$

where λ_m , $\boldsymbol{\gamma}_m$ and $\boldsymbol{\partial}_m$ are set of parameters to be estimated for the socio-demographic, latent effects explaining the latent variable m and the objective constraints that can influence the latent perceptions. Finally, θ_m is a constant, and $\omega_{m,n}$ is a normally distributed error term for latent variable m with zero mean and standard deviation σ_{ω_m} . In the most general cases, the latent variables can be correlated among them. Given the additional random term in the utility function, the probability that individual n will choose the sequence of choices is the same as in equation (7) but still conditional on ω . The unconditional probability is computed as the integral over the distribution of β, ω :

$$P_{in} = \int_{\beta, \omega} \prod_{t=1}^T P_{int}(\beta_{in}, \omega_n) \prod_{m=1}^M f_{x_m^*}(\omega) \prod_{r=1}^R f_{I_{rm}}(I_{rmn} | \omega_m) f(\beta) f(\omega) d\beta d\omega \quad (16)$$

The unconditional probability includes the distribution of a set of indicators, which are indicators of the latent variables. The *measurement* equations for the indicators are given by:

$$I_{rm,n} = \delta_{rm} + \alpha_{rm} \cdot X_{m,n}^* + v_{rm} \quad (17)$$

where $I_{rm,n}$ is one of $r = 1, \dots, R$ indicators for individual n and latent variable m . δ_{rm} is a constant in the measurement equations for latent variable m and indicator r , while v_{rm} is a normally distributed error term for indicator r and latent variable m with zero mean and standard deviation σ_{v_m} . Finally, α_{rm} is a coefficient associated with $I_{rm,n}$, i.e. the parameter for latent variable m on indicator r .

Due to assumptions of the distributions of the error terms, the distribution of the latent variable and the indicators are:

$$f_{x_m^*}(\omega) = f_{x_m^*}(X_{m,n}^* | X_{m,n}; \lambda, \sigma_{\omega}) = \frac{1}{\sigma_{\omega}} \Phi \left(\frac{X_{m,n}^* - (\theta_m + \lambda_m \cdot \mathbf{S}_n + \boldsymbol{\gamma}_m \cdot \mathbf{X}_{m,n}^{**})}{\sigma_{\omega}} \right) \quad (18)$$

$$f_{I_{rm}}(I_{rmn} | X_{nm}^*; \alpha_m, \delta_m, \sigma_{v_m}) = \frac{1}{\sigma_{v_m}} \Phi \left(\frac{I_{rm,n} - (\delta_{rm} + \alpha_{rm} \cdot X_{m,n}^*)}{\sigma_{v_m}} \right) \quad (19)$$

where Φ is the normal standard distribution. For an in-depth description of the theoretical foundation of discrete choice models, I refer to Walker (2001).

Note that for identification, one constant and one parameter should be normalized across the structural and measurement equations for each latent variable. More specifically, among the constants, $\theta_m, \{\delta_{1m}, \dots, \delta_{Rm}\}$ one should be normalized to zero, while among the parameters, $\omega_{m,n}, \{\alpha_{1m}, \dots, \alpha_{Rm}\}$ one should be normalized to 1. In this study I normalize δ_{1m} to zero and α_{1m} to one as commonly done in practice.

3.4 ESTIMATION

A common estimation technique for discrete choice models is maximum likelihood estimation, in which the parameters are estimated in order to maximize the product of the probabilities (or a logarithm transformation of them), i.e. maximize the likelihood across all observations. If the integral has a closed form (e.g. the MNL model), the estimation can be solved analytically, thus the log-likelihood can be computed as:

$$\mathcal{LL} = \sum_{n=1}^N \sum_{t=1}^T d_{int} \ln(P_{int}) \quad (20)$$

$$\text{where } d_{int} = \begin{cases} 1 & \text{if } i \text{ chosen} \\ 0 & \text{otherwise} \end{cases} \quad (21)$$

In cases where the integral is not closed form, like in the ML model, the estimation cannot be solved analytically, due to assumption about the distribution of random components. Instead it is common practice to rely on simulation techniques, such as the Maximum Simulated Likelihood (MSL). The concept is the same, hence we still seek to find parameter estimates that maximize the objective function, but since the integral cannot be solved analytically, we instead take random draws from the error distribution. Thus we denote \check{P}_{int} as the approximate probability computed as the average across R number of draws of μ from the distribution $f(\mu|\theta)$. A high number of draws gives a better representation and thereby minimizes the approximation skewness, although the calculation time increases. The simulated log-likelihood is computed as (Train, 2009):

$$\check{P}_{int} = \frac{1}{R} \sum_{r=1}^R P_{int}(\mu^r) \quad (22)$$

$$S\mathcal{LL} = \sum_{n=1}^N \sum_{t=1}^T d_{int} \ln(\check{P}_{int}) \quad (23)$$

Estimating models with latent variables is more complex than for the ML, due to the requirement of measurement indicators. They can be estimated in several ways (Walker, 2001), although two approaches are predominant (Raveau et al., 2010), i.e. sequential estimation and simultaneous estimation. The sequential estimation approach relies on separate estimates of the structural equation models of the latent variables, which is then estimated in the choice model, while the simultaneous estimation approach estimates the latent variables and the choice models jointly.

Models that allows for simultaneous estimation of LVs combine the traditional DCM with MIMIC models to perform a simultaneous estimation, and are referred to as Integrated Choice and Latent Variable (ICLV) models or Hybrid Discrete Choice (HDC) models or - in many cases - simply Hybrid Choice Models (HCM). The framework was originally proposed by Ben-Akiva et al. (1999) and later generalized by Walker (2001).

The sequential estimation is still a popular approach in the literature as it is clear and simple. However, the sequential estimation has a number of weaknesses: 1) potentially biased estimators which are not guaranteed to be consistent, and 2) underestimate the standard deviation of the parameters. The latter can manually be solved by a statistical correction of the variance of the estimated parameters (Topel and Murphy, 2002; Bahamonde-Birke et al., 2014), but this process is fairly complex, and thus rarely applied in practical used. The simultaneous estimation solves the theoretical issues of the sequential model, but has the disadvantage of being extremely complex and very computational demanding to estimate due to the unclosed integral for each latent constructs (in addition to the DCM itself).

4 DATA COLLECTION

The data collection process is an important but also challenging part of the analysis. For the choice of departure time it is challenging because the decision on when to depart depends on other choices and external factors. My data collection will include four main components: *i*) data that represent trade-offs with respect to level-of-service attributes and the departure time choice, *ii*) data which relate trips and activities to a daily activity schedule framework and derived constraints, *iii*) psychological elements related to individuals and how this relates to the theory of planned behaviour, and *iv*) data that represent individual characteristics.

In the case of departure time choice, as for many other phenomena, revealed preference (RP) data in many ways represent a preferable data foundation as these data contain information on the actual behaviour of individuals. However, RP data have some drawbacks as well. Firstly, in RP data it can be difficult to measure specific attributes (Louviere et al., 2000), and the data may contain little variation in the trade-offs between choices which in turn can make the model estimation potentially challenging. In particular in departure time studies it might be difficult to measure level-of-service attributes for the non-chosen alternatives accurately, especially travel time. A second important drawback of the RP data is that RP data lack the ability to investigate alternatives which are currently not available (Hensher, 1982; Louviere and Hensher, 1983) or are different from the existing ones (Hensher and Louviere, 1983). This point is particularly relevant in departure time studies when for example the goal is to study the influence of introducing a toll cost or congestion charging schemes. This is an aspect that nowadays is very relevant and debated among researches and has been put into practice in many cities around the worlds. This discussion is particularly relevant for Copenhagen, where a road pricing/toll ring has been highly debated for many years and is still a hot debate (Nielsen and Kristensen, 2011; Kristensen and Nielsen, 2012).

For these reasons, in the empirical application in this PhD thesis it was decided to use stated preference (SP) data in order to evaluate the introduction of a congestion price scheme. Furthermore, using SP data has some nice advantages such as being suitable for model-estimations since the experimental design can be designed to allow capturing multiple choices per respondent, making it a cost-effective way of collecting data.

However, SP data possess some serious limitations and challenges. The major weakness is due to the hypothetical nature of the SP questions and the potential lack of realism (Ortúzar and Willumsen, 2011). Recommendations to guarantee realism consist in considering a specific occasion rather than a general one, e.g. focusing on work trips in the morning rush hours made by car, and in general create realistic choice tasks that mimic the true characteristics of the choices faced by individuals. An important point in that respect is to ensure that individuals are exposed (during the SP exercise) to the same constraints as they face in real-life situations. In that situation they select an alternative considering the feasibility of that specific alternative in their real-life situation. This is particularly relevant in the departure time studies, because as discussed in the introduction, the choice of when to depart is likely to be linked to other activities in the daily schedule and potentially constrained by these.

When building the SP experiment in this thesis, particular attention has been given to the choice being realistic. To achieve that, survey respondents were asked first to describe the full trip/activity diary, and then subsequently for each trip/activity answer questions related to potential constraints (often not conscious) in their choice of departure.

The “framing” of the SP questions, e.g. asking about information related to the real trip prior to the SP experiment, is not new. However, “framing” in the context of detailed constraints is new. In trip timing, it is crucial to account for constraints affecting the time of departure. Since trips are performed in order to engage in certain activities (mandatory or not), trip timing constraints are commonly formed by activities. A straightforward approach used in the literature is to measure the constraint on the working time or more specifically, whether individuals have flexible or fixed working hours (de Jong et al., 2003; Hess et al., 2007b; Börjesson, 2007; 2008; 2009). However, as discussed in the introduction, departure time in the morning might be affected by the overall daily activity schedule, hence activities in the afternoon or evening might restrict (or at least partly influence) the remaining daily scheduling and as a result the departure time choices. Such dependencies can be complex and work in both directions in the sense that activities before as well as after work can influence the departure time for commuting trips. Furthermore, the restriction formed by each activity is likely to be determined by the type of activity, and the time when the activity is performed. In other words, specific activities might be constrained in different dimensions. This is important because the type of constraints affect the level of flexibility (or lack of same). One example is that escorting trips are constrained to a specific destination but then flexible in terms of which adult is performing the escorting activity. Another example is that shopping might not be bounded to a specific supermarket as well as to a specific day. A final example is that leisure trips may be optional all together. Such possibilities of changing plans are vital when coordinating the trip timing schedule.

The questions related to constraints refer to each and every activity performed outside home (even a very short one). In particular in the survey it was asked if the individuals could have changed their departure time to a later or earlier point in time. It was also asked if they carried out the activity at another location, at another time of the day, or another day or completely cancelled the activity, and whether someone else could have carried out the activity for her and if he/she decided what time to do the trip. Finally, questions related to the frequency of each trip and whether the trip was performed jointly with other individuals were also asked. These questions were used in the estimation of the departure time models (this is described in Paper 2, see Thorhauge et al., 2015a), but it also served as a question aimed at making individuals think and remember their daily activity plan and the related constraints before answering the SP experiment.

The SP experiment was customized by pivoting the values around the real trip (i.e. the real preferred arrival time) of each respondent. Using a reference alternative that connects to the experience of respondents has been recognized as important in a number of theories including behavioural, cognitive psychology and economic theories such as in prospect theory, case-based decision theory and minimum-regret theory (Rose and Bliemer, 2009). If the survey is conducted in one unique step (i.e., respondents are contacted only once), using a pivot design requires building as many SP designs as the number of possible real cases (i.e. combination of attributes) that can appear in the real trips described.

A pivoted fully efficient design was built, which has never been applied to departure time choices. A challenge in doing so is that attributes cannot be defined in isolation but must be considered in relation with other attributes, e.g. travel time must be defined in accordance with the time of departure. To deal with interdependencies among attributes, and to get a fully efficient design, we use pivoting around the preferred arrival time for each individual instead of around the actual departure time although the latter is more commonly applied in departure time SP studies. In this thesis, it is proved that these two methods are similar under the condition that the preferred arrival time and the actual trip are inside the rush hours (this is discussed in Paper 1, see Thorhauge et al., 2014a).

The efficient design was chosen for its desirable feature of minimizing the standard error of the estimates, thus lowering the number of respondents needed for model estimation. The advantages and disadvantages of an efficient design, compared to the orthogonal design which is more commonly used, have been discussed widely in the literature (Rose and Bliemer, 2009; 2013). However, more research is still needed to analyse the robustness of different designs and how robust efficient designs are with respect to misspecification of the prior parameters. A design is orthogonal if the attribute levels are balanced in the sense that each level within an attribute appears an equal number of times and all the attributes in the design are uncorrelated. This implies that the parameters can be estimated independently although this property does not extend to the non-linear models (ChoiceMetrics, 2012a). On the other hand, efficient designs aim to minimize the standard errors of the estimated parameters. Hence, efficiency is a measure of “goodness-of-fit” of the design (Kuhfeld et al., 1994). High efficiency equals low variance in the estimated parameters attainable with smaller sample size. Thus, given that the assumptions underlying the efficient designs prove correct, it will generally outperform the traditional orthogonal designs by attaining more accurate parameter estimates based on fewer observations (Rose et al., 2008; Rose and Bliemer, 2008; 2009; 2013). However, efficient designs need a prior knowledge of the estimated parameters which makes them sensitive to possible misspecification of the prior parameters, i.e. if the assumed prior parameters are not a good representation of the underlying true parameters. The importance of the prior parameters is highlighted by Rose and Bliemer (2009) who state that good information about the prior parameters is more important for minimization of the standard error than having a large sample size. Furthermore, efficient designs are also sensitive to a misspecification of the underlying model as well as the type of model (Bliemer et al., 2009; Bliemer and Rose, 2010). External Paper 2 (Walker et al., 2015) is concerned with a broader discussion and comparison of the robustness of different types of experimental designs.

The last part of the data collection is dedicated to measure the “latent individual effects”. These are effects that are not directly observable or measurable but on the other hand could influence the departure time choice. In recent years, it has become increasingly popular to account for psychological effects, such as attitude, but these studies have not been applied to the departure time choice. Arellana (2012) is the only one who has considered latent variables in the context of departure time choice, but he only considered attitude. However, studies have shown that numerous psychological effects can affect individual behaviour. In this thesis, following the Theory of Planned Behaviour (TPB), a set of 24 indicator statements was defined to help identifying the underlying psychological effects. Although the TPB is well established, the novelty of the application to the departure time choice makes the work challenging. Latent constructs (such as attitude towards being on time) need to be based on what is (or assumed to be) relevant for the choice context prior to defining the indicators. A great challenge in that respect has been to define those psychological elements that are most relevant to the choice of departure time. This is tricky as the human decision process is complex and cannot easily be summarized in just a few psychological constructs. However, we envisage that psychological elements regarding late arrival time at work is the most important factors. However, also constructs regarding travel time, flexibility and mobility is believed to be important for the departure time. A factor analysis performed with the collected attitudinal data confirmed that these intended latent constructs indeed hold.

The statements were measured using categorical responses, rated on an “agreement scale”, also commonly referred to as a “Likert scale”. Different approaches exist when defining the Likert scale. Some argue that the Likert scale should consist of an uneven number of categories, thus allowing the respondent a “neutral” option, while others argue that the Likert scale should consist of an even number of categories, thus forcing

the respondents to “choose side”. In line with that, some argue that there should be a “don’t know”/“not relevant”, to allow the respondents to “opt out”. The benefit of giving the respondents the option to opt out is to eliminate responses from individuals in which the statement is not applicable. However, the downside – and the reason why an “opt out” option was not presented – is that some respondents will select this option if the decision would require too much mental effort. Furthermore, including a “don’t know”/“not relevant” option would also increase the computational complexity, as these observations cannot simply be assigned a numerical value. To address this challenge great care was put in designing the statement (but also in defining the target sample) to make sure that all statement were relevant for all respondents. The data collected on the psychological dimension are described in detail in Paper 3 (Thorhauge et al., 2015d). For further documentation and description of the survey and data, see also Thorhauge (2015a; 2015b; 2015c).

5 SUMMARY OF PAPERS

5.1 PAPER 1: BUILDING EFFICIENT STATED CHOICE DESIGN FOR DEPARTURE TIME CHOICES USING THE SCHEDULING MODEL: THEORETICAL CONSIDERATIONS AND PRACTICAL IMPLEMENTATIONS

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This paper describes the methodology set up to collect data to study departure time choice and how this choice is affected by the daily activity schedule and constraints and by individual attitudes. In particular the paper discusses the problem of building an efficient design for the departure time choice. Efficient design allow using smaller samples, it is then interesting to investigate the possibility of also using them in the context of departure time choice. From a research point of view, using an efficient design for the departure time is challenging. The major problem is that in the departure time studies, attributes are interdependent and the design attributes presented to the respondents differ from those in the model, by which the design is created (Koster and Tseng, 2009), and this makes building the SP experiment quite difficult. The work of Arellana et al. (2012b) is the only example of an efficient design for departure time choice, but it uses a two-step design procedure, i.e. first fix one attribute, and define the remaining attribute values, and then in a second step, define the remaining attribute. However, this approach breaks the efficiency. In our study we propose using a pivot design around the preferred arrival rather than pivoting with respect to the actual arrival time. In short, the difference between the two methods collapses to a constant, which represents the difference (i.e. shift in time) between the preferred arrival time and actual arrival time (Thorhauge et al., 2013). To maintain realism in the choice task we restricted our sample to only include people who did go to work within the morning rush hours.

Another challenge related to the stated preference design is the need to customize the experiment specifically for each individual in order to guarantee realism of the attribute values. Customizing choice task to each individual requires prior knowledge of the level of service attributes for the current alternative. This is particularly challenging with efficient designs because it cannot be done in a single step, but it involves contacting the respondents at least twice: first to collect level of service attributes, then using these values to generate an efficient design for each respondent and then contacting respondents again to present the stated choice experiment. In order to be able to collect data in only one step, but keep the nice property of a customised stated choice experiment, we predefined a number of categories based on the travel time duration. A total of six different designs were then optimised (for TT equal to 10, 20, 30, 40, 50, and 60 minutes) and respondents were presented with the design closest to their reported travel time in the trip diary.

The stated preference experiment included three departure time alternatives, and four attributes: departure time, travel time, travel cost and travel time variability. Each attributes has three levels, except travel cost which has four. Following the approach in Arellana et al. (2012b), the travel time variability was included as an unexpected delay once a week. In particular, we defined the travel time variation as the travel time that

individuals experience once a week, hence with a 20% probability. The efficient design was constructed using the software package Ngene (ChoiceMetrics, 2012b). The design was generated using a D-efficient swapping-algorithm. For each of the 6 predefined travel time groups an efficient SP-design was generated with a total of 27 choice tasks divided into 3 random blocks. Hence, each respondent were presented with a total of 9 choice tasks. Ultimately, we managed to construct an efficient design pivoted around a reference trip for departure time choice modelling.

5.2 PAPER 2: HOW FLEXIBLE IS FLEXIBLE? ACCOUNTING FOR THE EFFECT OF RESCHEDULING POSSIBILITIES IN CHOICE OF DEPARTURE TIME FOR WORK TRIPS

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This paper discusses the problem of how to measure flexibility in the context of departure time and the effect of constraints imposed by other activities realised during the entire day. Previous studies have included arrival time constraints at the work place, either by asking 1) if the time when the work starts or ends is fixed or flexible, or 2) by asking if the respondents had any arrival time constraints. However, departure time choice is not only related to the main work activity itself, but also to activities realised before and after work, including intermediate stops to and from work. In this paper we pose three research questions. Firstly, we test whether the established ways (i.e. working hour start time and arrival time constraints at work) of measuring flexibility is enough to reveal the true constraints in the choice of departure time. Secondly, we test whether other activities realised during the day will affect the Willingness to Shift (WTS) and Willingness to Pay (WTP) for the working trips and especially for an individual with flexible working time. Thirdly, we test whether constraints on other activities throughout the day will cause the WTP to increase as it represents an extra cost.

To test our first hypothesis we collected information on arrival time constraints at work in two ways: 1) by asking if the time when the work starts or ends is fixed or flexible, and 2) by asking if the respondents had any arrival time constraints. Models were estimated using both information and the results were compared. To test our second and third hypotheses we collected detailed information regarding the respondents' full daily activity/trip schedule and the restrictions of these activities. Two indexes of *trip* and *activity pattern complexity* were built to test the effect of the daily activity schedule, while the type of restrictions considered includes temporal, spatial and social constraint for activities.

Our results suggest that the way information regarding flexibility is asked (i.e. as *fixed/flexible* or *restriction* or *no restriction*) does not seem to affect modelling results and can be used interchangeably as done in the current literature. However, the t-test for equality between coefficients clearly shows that, in our dataset, the information on whether individuals have restrictions or not at work allows capturing the re-scheduling penalties better. More importantly, these results show that information on fixed/flexible working hours does not allow revealing differences in preferences for scheduling delays later.

Regarding the second and third research questions, our results show that both the presence of other non-work activities during the day, but also if these activities are constrained, affects individuals' preferences and thereby their WTP. This was especially evident for individuals with *flexible* working time, which seem more likely to be restricted by other non-work activities, rather than by the work activity itself. This effect is particularly relevant for the *other* activities realised in non-working tours (namely home-based tours realised before going to or after coming back from work). In particular, it is clear that the penalty to reschedule the departure time is due to leisure activities being spatially or socially constrained and realised in the tour after coming back from work.

Finally, we applied a policy scenario in which a toll ring was introduced. Congestion charging is ranged between 20 DKK in the most congested time periods, to being free outside the rush hours. The congestion charge range was inspired by other Scandinavian cities which have already implemented congestion charging (Transportstyrelsen (SE), 2015a; 2015b). For the forecast, we obtained LoS-data for the non-choose alternative using the National Transport Survey (see Thorhauge, 2015d). We found that, on average, flexible individuals are twice as likely to reschedule to a departure time before 7:00 or after 9:00 as inflexible individuals.

5.3 PAPER 3: PSYCHOLOGY MEETS MICROECONOMICS: ACCOUNTING FOR THE THEORY OF PLANNED BEHAVIOUR IN DEPARTURE TIME CHOICE

Authors: Mikkel Thorhauge, Sonja Haustein, and Elisabetta Cherchi

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This paper discusses the important problem of accounting for the effect of underlying psychological aspects of the individual behaviour in the choice of departure time. The problem of integrating psychology and micro-economic theory is nowadays a key topic. There are already several evidences in different choice contexts, but so far the departure time choice has been studied from a micro-economic perspective. Indeed, the departure time is a kind of choice that can be strongly affected by psychological effect because the choice of departure time is highly affected by elements such as lateness penalties and risk awareness. Both are elements which are related to underlying psychological effects, which are difficult to measure, such as individual attitude and perception as well as social norms (e.g. work ethics among colleagues). Thus, we believe it is important to explore the problem of the departure time choice from a different perspective than the micro-economic theory and ultimately to understand to which extent individuals' departure time choice is driven by psychological and/or micro-economic aspects.

Almost all the studies within discrete choice modelling integrate only the effect of latent attitudes and (in some cases) perceptions. However, psychological aspects of the individual behaviour are much more complex than only attitudes, and ultimately accounting for these effects in a discrete choice framework is believed to be important. In order to do so we rely on the *Theory of Planned Behaviour* (TPB). This is one of the most well-established psychological theories, in which intention is a direct predictor of behaviour. Intention is then explained by a set of lower level psychological constructs, more specially the *attitude*, the *subjective* (social) *norms* and *perceived behavioural control* (PBC). In addition to that, PBC may also influence the choice directly. A great advantage of relying on the TPB is the firm theoretical foundation within the psychology literature. To our knowledge no one has accounted for the TPB in a discrete choice framework.

In this paper we first provide an in-depth discussion of the latent variables that can affect the departure time choice. Based on this theoretical discussion, specific data were collected to measure the following latent effects: *attitude* (towards flexibility, being on time, and having short travel time), *subjective* (social) *norm* and *personal norm* (towards being on time), *perceptions* (towards being on time, and mobility necessities), and finally *intention* (towards being on time). Based on a factor analysis we found that the collected data supported these latent constructs, albeit attitude towards being on time, personal norm and intention could be grouped. However, we decided not to collapse these latent variables (especially attitude and intention) into one in order to enable us to explore the psychological influence in accordance with the TPB.

Finally, to test the effect of the full TPB on the discrete choice of the departure time, we estimated hybrid choice models (HCM), accounting also for panel effects among the tasks of the stated choice experiments. HCM are complex models and estimation becomes more difficult as the number of latent effects increases. Since the objective of this paper was to discuss and define the TPB structure for departure time choices, we decided to use a sequential estimation. Although this procedure cannot guarantee unbiased estimators, Raveau et al. (2010) showed that the difference compared with the simultaneous estimation method is little.

Thus, this method was preferred in order to facilitate model estimation of a broad spectrum of psychological elements.

Our results confirm that accounting for the TPB significantly improved model estimation, compared with a traditional DCM without latent variables. From the phenomenon point of view, we found that accounting for the full theory of planned behaviour is important, as individuals who value to be at work on time are less likely to reschedule – especially to a late(r) departure time. We also found that perceived mobility necessities (PMN) and attitude towards having a short travel time influenced the choice and improved the model significantly.

Finally, we also found that accounting for latent effect was important when considering fixed and flexible working hours. More specifically, we found that the penalty of late arrival for individuals with fixed working hours is higher than for individuals with flexible working hours. Similarly, we found that individuals with flexible working hours value having a low travel time higher.

5.4 PAPER 4: THE EFFECT OF PERCEIVED MOBILITY NECESSITY IN THE CHOICE OF DEPARTURE TIME

Authors: Mikkel Thorhauge, Elisabetta Cherchi and Jeppe Rich

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In this paper we continue to investigate the effect of the latent psychological aspects on the discrete choice of departure time, but we focus specifically on the effect of *Perceived Mobility Necessities*, which is a relatively unexplored psychological effect – especially in a discrete choice context, and even more within departure time. More specifically, to our knowledge, Arellana (2012) is the first – and so far only one – to account for attitudinal effects for departure times modelling. However, no one accounted for non-attitudinal latent elements. Thus this study is the first to explore the latent influence of *perception* (and more generally, a non-attitude latent variable) with respect to departure time models using a simultaneous estimation.

In Paper 3 (Thorhauge et al., 2015d) we showed that *Perceived Mobility Necessities* (PMN) were found to be significant in explaining departure time behaviour. However, in Paper 3 the influence of PMN was found using sequential estimation, which may produce inefficient and potentially biased estimates (Topel and Murphy, 2002; Yáñez et al., 2010; Bahamonde-Birke et al., 2014). In this paper the goal is to estimate PMN using a simultaneous estimation approach. For this reason we relied on the hybrid choice framework (Walker, 2001).

Our results show that it is indeed relevant to extend the original theory of the scheduling model to incorporate effects of individuals' perception which is not directly measurable. More specifically, we found that individuals who have a high perceived mobility need dislike to reschedule their departure time, and especially dislike late departure. This finding is reasonable as individuals who have a high agreement with the indicators, and thus perceive they have a high mobility need, also in general have more activities, while individuals with few trips in general have a low perceived mobility necessity. The results in this paper make sense as individuals who have many trips, are also less willing – or able – to reschedule their departure time. Finally, it is important to note that as panel effect is accounted for, the estimates of PMN lose significance. This indicates that PMN (at least) partly account for panel effect among individuals. However, it is likely that a larger sample size would address this problem. Nevertheless, more research is needed to fully understand the effect of PMN. Overall, this paper shows that not only attitude (which has gained a lot of attention in recent research within discrete choice models) affects people's decisions, but also individuals' perception. In Paper 5 (Thorhauge et al., 2015b) we explore the impact of the latent constructs, and more specifically the TPB, within a simultaneous hybrid choice model framework.

5.5 PAPER 5: THE ROLE OF INTENTION AS MEDIATOR BETWEEN LATENT EFFECTS AND CURRENT BEHAVIOR: APPLICATION OF A HYBRID CHOICE MODEL TO STUDY DEPARTURE TIME CHOICES

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Previous literature – as well as findings from the previous papers of the thesis – provides evidence of the importance of accounting for psychological effects. More specifically, in Paper 3 (Thorhauge et al., 2015d), we showed that accounting for the full theory of planned behaviour is important in the context of departure time, but we used a sequential estimation which potentially can cause bias estimates. In Paper 4 (Thorhauge et al., 2014b), we use a simultaneous estimation, but we focus on only one latent effect: we explore the impact of accounting for perceived mobility necessities. Besides Arellana et al. (2012), this is the only example of accounting for psychological elements in discrete choice models of departure time. However, we know from the psychological literature that the underlying constructs are much more complex. This paper is the first evidence of accounting for the full Theory of Planned Behaviour estimated simultaneously in the context of departure choice modelling – and to our knowledge – in discrete choice models. The objective of this paper is to extend the work on Hybrid Choice Models (HCM) by (1) assuming that intention affects the marginal utility of the scheduling attributes (and not only the preference for departing early/late), and attitude towards short travel time and PMN affect the marginal utility of travel time (2) exploring the role of objective constraints in the perceived control, (3) using a simultaneous estimation approach, and (4) testing the impact of accounting for all these effects in prediction.

We found that several latent variables were significant – and correct sign. In accordance with the TPB we were also able to combine latent constructs in a hierarchical structure in which attitude subjective norm and perception influenced the intention towards being at work on time, which ultimately influenced the choice. Furthermore, we also included attitude towards having a short travel time directly in the choice alongside Intention. We interacted *Intention* with all scheduling variables, i.e. *Scheduling Delay Early* (SDE) and *Late* (SDL), and also a *discrete lateness dummy* (DL), while *AttTime* was interacted with the *travel time* (TT). We found that both *Intention* and *AttTime* were statistical significant in explaining the choice, and furthermore *AttLate*, *SN* and *PBC* were highly significant in explaining the *Intention*. We also tested the LV summed in the utility specification, but less significant results were obtained (Thorhauge et al., 2015c). Also, the interaction between the Level-of-Service (LoS) variables and the latent variables indicate that the psychological elements do indeed influence the individuals' preferences. We found all our core parameters (i.e. in the scheduling model) to be stable, highly significant, and have the correct sign, with the exception of the parameter for DL for individuals with no arrival constraints at work (which were not statistically significant).

We compared the hybrid choice model with a traditional scheduling model (SM), i.e. without latent variables, in some forecasting scenarios (Thorhauge, 2015d) in which we modified both the *transportation*

system and the *activity system*. As expected, we found that on an overall scale the SM and HCM had similar substitution patterns. However, when exploring the forecasting results in more details, we noticed that the HCM allows forecasting in greater details among specific groups within the sample, which is not possible with the traditional SM. More specifically, the structural equations include socio-demographic variables which were not statistically significant when included directly in the discrete choice utility, but only when included indirectly through a latent variable, hence the HCM allows to measure diversity among different subsamples.

Ultimately, this result provides empirical evidence of the importance of the TPB within a micro-economic framework, more specifically departure time. This is an interesting finding as it is not only statistically significant within a discrete choice framework, but also theoretically firmly grounded in the psychological literature which has acknowledge the importance of the full theory of planned behaviour for years.

6 CONCLUSION AND PERSPECTIVES

Congestion is an increasing problem in most major cities. An effective way to reduce the level of congestion is to control – or motivate – individuals to shift away from the peak. In doing so, it is important to understand what affects individuals' choice of departure time for the morning commute trips. This PhD dissertation contributes to the research in the following ways:

Firstly, it provides evidence of a fully D-efficient stated choice design for a departure time context. Building efficient designs is a complex task. Especially for departure time choices designing stated preference experiments is challenging, mainly for two reasons: 1) due to the interdependence among attributes in the design phase, and 2) due to the effort of ensuring realism within the choice task. The latter part was done using a pivot design around a reference trip (usually from the day before). The D-efficient design performs well and parameter estimates are highly statistically significant, with correct signs, and reasonable magnitude. Furthermore, in External Paper 2 it was found that the efficient design performs well provided good prior knowledge about the parameters is available, but at the same time it is sensitive to a misspecification of the prior parameters. To dampen the sensitiveness towards a misspecification one could rely on Bayesian efficient designs. However, taken the complexity of efficient and Bayesian efficient designs into consideration, one might be better off creating a (non-dominated) random design.

Secondly, the thesis investigates the impact of accounting for a full activity schedule, and more importantly, constraints associated with every single trip and activity. It shows the importance of taking the full activity schedule into consideration. In particular, simply asking respondents if they have fixed or flexible working hours might not be enough as their true flexibility might be affected by constraint at work, or constraints from intermediate stops to and from work. It is important to note that in the current framework of the thesis I only consider the trip timing decision regarding the morning commute to work, taking into account how constraints in the remaining activity schedule affect that decision. However, I do not explicitly model the departure time options for the remaining trips in the activity schedule, but it would be an interesting – and natural – extension to the current modelling framework. Even further down the pipeline, adding household interaction and social coordination could be very interesting, indeed. Ultimately, it would be an interesting dimension to extend the framework to cover multiday decisions, to explicitly capture day to day variation, possibly in a weekly or monthly rhythm. Especially the specific constraint from different types of activities might vary across multiple days in a systematic way (e.g. soccer practice every Tuesday and Thursday), or in a non-systematic way (e.g. ad hoc meetings), or something in between (e.g. you share the escorting responsibility of children evenly with your spouse, although these trips may be negotiated with the spouse). During the PhD it was not possible to collect the data to perform multiday analysis for departure time choices, however it is considered an interesting extension for further work.

Thirdly, the thesis shows the importance of accounting for psychological elements in choice modelling. More specifically, it shows that the Theory of Planned Behaviour (TPB) does indeed play an important role in the context of departure time. This is highly interesting as it provides the first evidence of the effect of accounting for the full TPB within a discrete choice framework, and more specifically, within a departure time context. This is an important finding for a number of reasons: 1) it shows that other latent constructs different from attitude is also important to take into considerations, 2) it provides some evidence that the psychological effects in discrete choice models are much more complex than previously assumed, thus the latent constructs should be defined as a hierarchical structure, since many latent variables, such as attitude, norms and perceptions, affect the choice indirectly through intention. The strength of the TPB is that it is

firmly grounded within the psychological theory. In addition to that, I also found some latent variables affecting the choice of departure time directly. More specifically, I found that attitude towards having a short travel time and Perceived Mobility Necessities (PMN) also played a role in shaping individuals preferences.

Finally, preliminary work has been done to estimate a latent class departure time model. We see a great potential in applicability of such a model framework, as it is envisaged that latent groups of individuals (with similar preferences) exist. Such groups can be defined in various ways to capture different aspects of individuals' lifestyle (e.g. household composition and location, types of activities and job, etc.). Furthermore, an interesting extension is to use the latent variables, more specifically the TPB, to help defining the class membership model. Hence, a latent class departure time model is also considered as an interesting topic for further research.

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Building efficient stated choice design for departure time choices using the scheduling model: Theoretical considerations and practical implementations

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Abstract

Modelling departure time is an important step in forecasting traffic demand. The purpose of this research is to contribute to the data collection field when studying departure time choices. Differently from the majority of the previous studies we used an efficient stated preference (SP) experiment. A main benefit of using an efficient design is that it allows using smaller samples. However, building experimental designs for the departure time is challenging for two main reasons: 1) interdependence among attributes, and 2) realism in the choice tasks. To ensure realism, we customized the choice task based on the trips described by each individual in a trip diary and on the departure time needed in order to be at work at their preferred arrival time. However, with efficient designs it is not possible to customize the SP for each individual, unless the real trips are known before optimizing the SP design. To overcome this challenge, six different designs were constructed based on predefined travel times (10, 20, 30, 40, 50, and 60 minutes). Respondents were presented with the design which was closest to their reported travel time in the trip diary. The design was simulated using almost 20.000 observations, and was adjusted until the design was stable and the prior parameters could be recuperated.

Keywords: data collection, stated preference, experimental design, efficient design, departure time choice.

1 Introduction

Congestion is an increasing problem, and the time of departure (especially in rush hours) becomes more and more crucial in terms of avoiding congestion. This makes it increasingly important to study departure time choice, especially morning commute trips to work. When doing so, the scheduling model (1982) is often used. The scheduling model is based on the bottleneck theory (Vickrey, 1969), and consist of a trade-off between travel time and penalties for rescheduling, i.e. being early or late.

However, an equally important part of studying departure time choice is the data collection, as the data quality is of crucial importance in the modelling phase. The purpose of this paper is to describe the entire process of how the data was gathered from design to data collection, and discuss upsides and downsides when applied to our empirical departure time study in the Greater Copenhagen Area.

Departure time have been studied using both revealed preference (RP) data (Coslett, 1977; Small, 1982; Hendrickson & Planke, 1984; Small, 1987; Chin, 1990; Small et al., 1995; 1998a; Bhat, 1998b; 1998c; Steed & Bhat, 2000a; 2000b; Bhat & Steed, 2002), stated preference (SP) data (de Jong et al., 2003; Ettema et al., 2004a; 2004b; Hess et al., 2007a; 2007b; Tseng & Verhoef, 2008; Börjesson, 2007; 2009; 2012; Arellana et al., 2012), and some studies estimated models based on joint RP-SP data (Börjesson, 2008; Kristoffersson, 2011; Tseng et al., 2011; Koster & Verhoef, 2012). Both have advantages and disadvantages. The advantages of RP data is that it captures actual behavior, thus is less sensitive to the distortion that can occur using SP-data. On the other hand SP-data consists of hypothetical trade-offs, which makes them particularly useful for model estimation, since they can be designed with sufficient variation to enable good model estimates. In addition to that, SP-data allows for inclusion of alternatives which are currently not available (Hensher, 1982; Louviere & Hensher, 1983) or different from the existing ones (Hensher & Louviere, 1983). Studies have shown that individuals are capable of dealing with the hypothetical nature of SP-data (Louviere et al., 2000). For an in-depth discussion of advantages and disadvantages of RP and SP data see e.g. Adamowicz, Louviere & Williams (1994) and Hensher (1994).

When building SP experimental designs it is common practice to do so by defining a set of alternatives, attributes and different levels (i.e. values) of the attributes. The *full factorial design* consists of all possible combination of choice sets. However, normally the full factorial design is extremely large, hence making it impractical (or impossible) to cover all possible combinations of choice tasks. Therefore, common practice is to select a subsample of the full factorial design to be used, i.e. a *fractional factorial design*. Another benefit of sampling choice task is to avoid choice sets where one alternative is dominant, i.e. better across all attributes.

Traditionally *orthogonal design* was the main way to build experimental stated preference designs. A design is orthogonal if the attribute levels are balanced and all the attributes in the design are uncorrelated, i.e. that the parameters can be estimated independently (ChoiceMetrics, 2010). However, in recent years, a new design method has gained popularity, i.e. *efficient designs*, which build upon the idea first presented by McKelvey & Zavoina (1975). The objective in an efficient design is to minimize the standard errors. However, Kuhfeld et al. (1994) stress the importance of not categorizing a design as being efficient or not, but treat efficiency merely as a measure of “goodness” of the design. High efficiency equals low variance in the estimated parameters. For simplicity, however, we will refer to designs which aim to minimizing the standard errors as “efficient designs”. The advantage of efficient designs is that it - given the right prerequisites - outperforms the traditional orthogonal designs, see Rose & Bliemer (2007), Rose et al. (2008a), and Rose & Bliemer (2009). Another - and more practical - benefit of the efficient design is that smaller sample size is needed compared to orthogonal design all else equal (Rose & Bliemer, 2009; 2013). The downside of efficient designs is that they are normally more complicated to build. Another disadvantage in the efficient design is the need of a prior knowledge of the estimated parameters, which is not always easy to obtain – and this makes the design sensitive to a misspecification of the priors parameters, i.e. if the assumed prior parameters is not a good representation of the underlying true parameters. The importance of the prior parameters is highlighted by Rose & Bliemer (2009), that states

that good information about the prior parameters are more important for minimization of the standard error than having a large sample size. Hence, having a fixed pool of money to conduct a survey, Rose & Bliemer (2009) recommends to (spend some of the money to) conduct an initial pilot study in order to obtain information about the true (and thus the prior) parameters, rather than spending all the money for the final sample (thus having prior parameter information of lesser quality and precision). For a detailed theoretical and practical walkthrough of how to construct both orthogonal and efficient designs we refer to the Ngene-manual (ChoiceMetrics, 2010).

Another important aspect of departure time choices is whether to treat time as continuous or discrete. Despite that time by nature is continuous, it can be argued that people (when dealing with departure time) perceive time in rounded intervals. A discretization of time has the further advantage that it allows to utilize the well-known field of discrete choice models. Within departure time some studies have treated time as continuously (Mannering et al., 1990; Mahmassani et al., 1991; Hamed & Mannering, 1993), albeit the majority of studies have converted the choice into a discrete framework (Small, 1982; 1987; Hendrickson & Planke, 1984; Small et al., 1995; 1999; 2000; Noland & Small, 1995; 1998; Small & Lam, 2001; de Jong et al., 2003; Hess et al., 2007a; 2007b; Börjesson, 2007; 2008; 2009; 2012; Arellana et al., 2012; Lizana et al., 2013; Kristoffersson, 2013).

For this study it was decided to collect discrete Stated Preference data using an efficient design. This was done for a number of reasons:

- First of all, it was decided to discretize time mainly for two reasons: 1) even though time is continuous, people do not consider and differentiate every single second – or minute – but tend to treat time in rounded intervals (de Jong et al., 2003; Börjesson, 2007; Hess et al., 2007a) and 2) by consider time as being discrete it allowed us to utilize the toolbox of discrete choice models available to estimate models.
- Second, SP data was chosen since they possess several advantages over RP data that was considered highly desirable for this study: 1) the strength of SP data is that a high level of variation in the choice task can be insured, thus helping to improve model estimations later on, 2) the SP design allow to capture hypothetical choice situations, which allowed to include TC (as road pricing/toll ring in Copenhagen have been highly debated in Copenhagen in the previous year is still debated (Nielsen & Kristensen, 2011)), and 3) SP designs allows to collect multiple choice task per respondent, thus less individuals is needed in the data collection phase. In particular, this was important since the full questionnaire was very detailed, and thus very long, making it challenging to have individuals to complete the questionnaire. Therefore it was extremely valuable to be able to collect numerous choice tasks per respondents.
- Third and lastly, a strong motivation for choosing an efficient design was 1) for the purpose of research, since – to our knowledge – Arellana et al. (2011; 2012) are the only example of efficient design for departure time choice, however they use a two-step procedure that breaks the efficiency, and 2) an efficient at the same time will help in reducing the number of respondents needed, which, as mentioned previously, is a highly desired feature for this study.

Designing efficient SP surveys for departure time models is not a straightforward process for a number of reasons highlight later on. The purpose of this paper is to describe the process of creating the efficient stated choice design from start to end. The structure of the remaining of this paper is as follows. Section 2 will describe the general process of defining levels etc., while section 3 will focus specifically on the challenges faced in building stated choice designs for departure time models. Section 4 will cover the convergence process towards the final design, while section 5 will describe the remaining of the questionnaire as this is linked with the stated choice experiment. Finally the paper will summarize with the concluding remarks.

2 Modelling of departure time choices

When constructing an efficient design it is necessary to define the model specification prior to the design phase since the design is tailored specifically to the model specification. For that, we rely on the scheduling model (SM), which was first formulated by Small (1982), and have since been the dominant way of modelling departure time choice (Small, 1982; 1987; Hendrickson & Planke, 1984; Small et al., 1995; 1999; 2000; Noland & Small, 1995; Noland et al., 1998; Small & Lam, 2001; de Jong et al., 2003; Hess et al., 2007a; 2007b; Börjesson, 2007; 2008; 2009; 2012; Arellana et al., 2012; Kristoffersson, 2013). In the scheduling model it is assumed that individuals aim for a specific preferred arrival time (PAT) at the destination when choosing departure time, hence making it useful to model commuting trips, since most people (prefer to) go to work during the rush hours (Day et al., 2010). Ultimately, the scheduling model is based on the concept of trading between travel time and penalties for rescheduling, i.e. being early or late. The scheduling model assumes that travelers are faced with a discrete number of alternative departure times and they choose according to the following utility specification:

$$V_{jnt} = ASC_j + \beta_{TT} \cdot TT_{jnt}(DT_{jnt}) + \beta_{TC} \cdot TC_{jnt}(DT_{jnt}) + \beta_{SDE} \cdot SDE_{jnt} + \beta_{SDL} \cdot SDL_{jnt} \quad (1)$$

Where V_{jnt} is the utility for individual n associated to alternative j , in choice task t . TT is the total travel time from origin to destination, which in principle is a function of the departure time (DT), hence the notation $TT_{jnt}(DT_{jnt})$. Similar TC is the travel cost with respect to DT, while SDE and SDL are the scheduling delays, i.e. the cost of arriving early or late, respectively, and are defined as:

$$SDE_{jnt} = \max(-SD_{jnt}; 0) \quad \text{and} \quad (2)$$

$$SDL_{jnt} = \max(0; SD_{jnt}) \quad (3)$$

The Schedule Delay (SD) is defined as the difference between the Preferred Arrival Time (PAT) and the actual Arrival Time (AT) of alternative j , and AT must be equal to the departure time plus the total travel time, i.e. the SD for alternative j , individual n and choice task t is defined as:

$$SD_{jnt} = AT_{jnt} - PAT = DT_{jnt} + TT_{jnt} - PAT \quad (4)$$

If a traveler arrives at his or her preferred arrival time then SDE and SDL will be equal to zero. This yields that the individual will not experience disutility from rescheduling. However, TT is not constant, and it consists of different parts, as stated in Fosgerau et al. (2008):

$$Travel\ Time = free\ flow\ time + systematic\ delay + unexplained\ delay \quad (5)$$

An extension of the scheduling model acknowledged the fact that travel time variability (TTV) plays a role in the choice of departure time. Based on the literature travel time variability have been included in two distinct ways: 1) Expected travel time, and 2) mean variance. However, some authors (Noland et al., 1998; Small et al., 2000; Börjesson, 2007) recommend using the approach of expected travel time. Hence in this study the travel time variability is included as the expected travel time, $E(TT)$. Given a series of i different travel times for each alternative j and choice situation t , the expected travel time is the sum of the travel time weighted by the probability (p_i) that each travel time occurs:

$$E(TT_{jnt}) = \sum_{i=1}^I p_i \cdot TT_{jnti} \quad (6)$$

And equations (2) and (3) will be written as:

$$E(SDE_{jnt}) = \sum_{i=1}^I p_i \cdot SDE_{jnti} \quad (7)$$

$$E(SDL_{jnt}) = \sum_{i=1}^I p_i \cdot SDL_{jnti} \quad (8)$$

Note that $\sum_{i=1}^I p_i = 1$.

3 Design a stated choice design for the scheduling model

One of the most important aspects in generating the design (regardless of using an efficient or orthogonal design) is to ensure realistic attribute values in the choice task which are presented to the respondents, i.e. the travel time presented to the individuals in the choice task should be similar to the travel time that particular individual actually faces in real life. First step in achieving this for departure time studies is to customize the choice task specifically for each single individual based on his or hers travel characteristics (such as departure time and travel time), hence generating alternatives based on their actual trips. This can be achieved by using a pivot design, in which the alternatives are generated from a reference alternative (Rose et al., 2008b), i.e. their current commuting trip. According to Rose & Bliemer (2009), using respondent's experience (e.g. through a reference alternative) have also been recognized in a number of theories within both behavioral and cognitive psychology, but also within economic theories, e.g. prospect theory, case-based decision theory and minimum-regret theory.

However, in order to build a customized efficient pivot designs the travel characteristics (travel time and departure time) of the individual is required before hand. Since this would require the respondents to be contacted more than once (first to collect trip information, and later – after the efficient design have been generated based on the reference trip – to contact them again to answer the customized choice task), a 2-step data collection phase was not considered to be optimal. To avoid contacting the respondents multiple times, a number of “travel characteristic”-categories were predefined, and then each respondents were assigned to the group which were closest to his or hers travel characteristics. In that way it is possible to maintain a realistic choice set while instead using a 1-step data collection phase.

The downside of this approach is that the number of predefined groups quickly becomes rather large, making it very time-consuming to build efficient design for each specific groups. To reduce the number of predefined groups it was decided to pivot the design around the preferred arrival times instead of the actual arrival time. By pivoting around the preferred arrival time the number of categories collapses into far less predefined groups which are solely dependent on the number of intervals which are predefined by the travel time. In addition, if the actual arrival of the respondent is equal to their preferred arrival time, then the two methods are identical.

Finally, building the design around the preferred arrival time has an additional benefit, i.e. the trip which the individual reports might already be rescheduled (compared to the preferred/intended trip), and generating alternatives from a trip which is already rescheduled may potentially lead to an unrealistic alternative, which is far from the departure time that a specific individual might consider.

Below we will – given the framework outlined above – describes the choices made in building the efficient stated choice design, and more specifically how many (and which) departure time alternatives, attributes, levels, and prior parameters to use. Finally, we will also discuss the target sample to which the design is to be presented.

3.1 Alternatives

The *alternatives* represents the choices (i.e. the *choice set*) among which the respondent will make his or hers choice. When deciding on the number of alternatives to include, it is a balance between whether to construct a simple design with few alternatives or a more complex design with a higher number of alternatives. According to the micro-economic theory the choice set should be 1) exhaustive (i.e. include all available alternative), 2) mutually exclusive, and 3) differentiable. Hence according to point 1 this yields departure time alternatives which are (very) close to resemble continuous time, however, that would ultimately defeat the purpose of utilizing discrete choice models, and likely conflict with point 3. On the other hand, leaving out alternatives may cause the choice to be skewed.

Within departure time choice many studies have used binary choice designs, i.e. designs in which the choice set consists of two alternatives (Small et al., 1995; Hollander, 2006; Börjesson, 2007; 2008; 2009; 2012; Koster et al., 2011; Tseng et al., 2011). The main benefit of binary choice experiment is the simplicity

of the design, making it easier for the respondents to comprehend and evaluate the alternatives (and their attributes). However, recent literature indicates that respondents can comprehend rather complex designs (Chintakayala et al., 2009; Caussade et al., 2005), making use of (too) simple designs unnecessary (Hess & Rose, 2009). In fact, according to Hensher (2006) including all important alternatives may improve the data quality. Another study by Bliemer & Rose (2009) compared the results from different studies (of the same choice) with designs ranging between 18 and 108 alternatives. It shows that an efficient design with specific selected alternatives leads to smaller standard errors, than an orthogonal design with 108 alternatives. According to Hess & Rose (2009) this results indicates that a design with a high number of alternatives does not (necessarily) lead to a better model estimation, despite the theoretical foundation. Caussade et al., (2005) recommends to use four alternatives, as this seems to be the optimum tradeoff between simplicity and having a design covering the full choice set (in most cases), albeit to our knowledge Tseng et al. (2005) is the only study within departure time using four alternatives.

In this study it was chosen to follow the approach seen in Arellana et al. (2011; 2012) and Lizana et al. (2013), thus defining three departure time alternatives in each choice set. The reason for this is twofold: firstly the literature has shown that three alternatives are definitely not too many alternatives to allow the respondents to evaluate and compare the alternatives upon making a choice. Secondly three alternatives allow for an intuitive choice set structure, where respondents will be able to choose between departing around the same time as they would normally do, while offering two rescheduling alternatives – one departing earlier and one departing later. This setup was found to be intuitive. It is important to note that when presented to the respondents the alternatives were unlabeled, thus simply denoted A, B, C. This was done to avoid the choice to be affected by a prior preference without evaluating the characteristics of each alternative.

3.2 Attributes

Designing a stated choice design for the SM is complicated since the design attributes (which are presented to the respondents) and the model variables (which enters the utility function) is not a strictly one-to-one relation as seen in most choice situation (e.g. mode choice or route choice) (Koster & Tseng, 2009).

Design attributes Presented to the respondent	Model attributes Included in the model specification
<ul style="list-style-type: none"> • Departure time (DT) • Travel time (TT) • Travel time variation (TTV) • Travel cost (TC) 	<ul style="list-style-type: none"> • Expected Travel Time (ETT) • Expected Scheduling Delay Early (ESDE) • Expected Scheduling Delay Late (ESDL) • Travel cost

Table 1: Design and model attributes for the scheduling model (Koster & Tseng, 2009).

More specifically, in departure time choices attributes are interdependent. For example the travel time (TT) and travel time variability (TTV) is dependent on the departure time (DT). Similarly, the scheduling delay is dependent on TT, TTV and DT, as well as the preferred arrival time PAT, according to eq. (7) and (8).

Travel time variability can be presented in a variety of different ways. One way is to present day-to-day travel time variation (Koster & Tseng, 2009). Another way is to have a fixed travel time, with a travel time variability which occurs occasionally (e.g. once a week) as done seen in Tseng (2011) and Arellana et al. (2011; 2012). Finally TTV can be presented as a probability of being late as done by Koster (2011) in a study on departure times on trips to the airport.

In this study travel time variability are incorporated in the stated choice design by following the approach of Arellana et al. (2011; 2012) and (Tseng et al., 2011), using a deterministic probability of facing unexpected delays. This approach was chosen since TTV is not the main focus of this study, albeit we recognize that TTV can influence the departure time choice, and hence cannot be completely excluded. We defined the probability of being late to 20%, hence equivalent to being late once a week (assuming five working day per week).

3.3 Levels

A key element in designing the stated choice experiment is to define the *attribute level range*. Ultimately, the level values will determine the trade-offs respondents are facing when presented with the choice tasks. A high attribute level range is preferable from a theoretical statistical point of view. On the other hand, however, it is important to narrow the range of the attribute level to only consist of realistic values for the respondent, since although a wide attribute level range may improve the parameter estimation, the respondent will not (easily) be able to relate to attribute values which is too far away from their current trip.

Initially 5 levels were chosen for all attributes as seen in a previous study by Arellana et al (2012). However, the fully efficient design in this project gave cause to complexities and computational problems. The computational problem was mainly due to a high number of constraints needed in the design script. The constraints are needed to ensure that the interrelation between attribute levels match according to the conversion needed between design attributes (for which the levels are defined) and model attributes (for which the efficient design is generated), as highlighted in table 1. To overcome these problems the number of levels were reduced to three levels for DT, TT, and TTV. Since TC didn't give rise to the need of any constraints, this attribute was unaffected, but it was chosen to reduce the number of levels for this attribute as well in order to have a more "equal" design among the attributes. Ultimately we selected to have four levels for TC. The final level values are discussed later.

3.4 Choice task

One of the benefits of SP-data is the ability to collect numerous choice tasks per respondents. In our design we needed a minimum of 25 choice tasks due to the restrictions formed by the constraints mentioned above. According to Bliemer & Rose (2009) stated choice experiments have been conducted ranging from 1 to 25 choice tasks per respondent, so it might be possible to have one respondent answering all 25 choice tasks. However, we did not think it was feasible to present each respondent with a total of 25 choice tasks, since the questionnaire is quite time consuming. Other departure time studies who have relied on SP-data have presented the respondents with a total of 8 (Börjesson, 2007; 2008; 2009; 2012), 9 (Small et al., 1995; Noland et al., 1998; Hollander, 2006), 10 (Koster et al., 2011; Tseng et al., 2011), 11 (Tseng & Verhoef, 2008), 13 (Arellana et al., 2012), 15 (Tseng et al., 2005), or 16 (de Jong et al., 2003) choice task per respondents. Ultimately, we decided to use a blocking design with a total of 27 choice task, hence three blocks consisting of 9 choice task (per respondents).

3.5 Prior parameters

As briefly mentioned in the introduction, when building efficient designs the aim is to minimize the standard error of the parameters in the model specification. This is done by utilizing the asymptotic variance-covariance (AVC) matrix. The AVC matrix can be derived if the parameters are known. However, the purpose in the modelling phase is to estimate the parameters, hence these are not known. To overcome this problem the efficient design makes use of (some level of) prior parameter information as a best guess towards the true parameters. Different strategies exist when defining the prior parameter (Rose & Bliemer, 2009). The first methods assume the parameters equal zero. The second method assumes that the prior parameters are non-zero and known with certainty, hence a single value is assumed for each parameter. The third method (known as Bayesian efficient designs) was introduced by Sándor & Wedel (2001) and relaxing the assumption in the second method, by assuming the prior parameters as a distribution (Bliemer et al., 2008). Finally, a fourth method is proposed by Kanninen (2002), in which the design is updated during the collection phase as the knowledge of the true parameters increase. It goes without saying that, the better information about the prior parameters, the better the efficient design will perform, hence assuming all prior parameters to zero was quickly ruled out. Due to the difference in the model and design attributes in departure time choices, method three and four were disregarded in order not to complicate unnecessarily. Instead we relied on previous departure time studies to help define the prior parameters.

Based on previous departure time studies it should be expected that $0 > \beta_{SDE} > \beta_{TT} > \beta_{SDL}$, or at least $0 > \beta_{SDE} > \beta_{SDL}$ (Hendrickson & Planke, 1984; de Jong et al., 2003; Hess et al., 2007a; 2007b; Börjesson, 2007; 2008; Asensio & Matas, 2008; Koster et al., 2011; Arellana et al., 2012; Koster & Verhoef, 2012). The signs of all the parameters are expected to be negative; hence an increase in e.g. travel time would decrease utility. In addition, Börjesson (2009) made a meta-analysis of the ratio of parameters of SDE and SDL with respect to the parameter for TT, as seen in table 2. These ratios were then sought to be maintained in the calibration process of the design. Different prior parameters were tested in the calibration phase. The prior parameters used in the final design will be discussed in section 4.

Studies	SDE/TIME	SDL/TIME
Small (1982), commuters	0,61	2,40
Noland et al. (1998), commuters	0,97	1,31
Dutch, commuters, flexible hours	0,89	0,63
Dutch, commuters, fixed hours	0,72	1,17
Dutch, other trips	0,96	0,94
West Midlands, commuters, flexible hours	0,77	0,79
West Midlands, commuters, fixed hours	1,70	7,15
West Midlands, other trips	0,67	0,87
Present study, commuters, flexible hours/ other trips	0,80	0,82
Present study, commuters, fixed hours/ school trips	1,47	3,38
Present study, business trips	0,71	1,06
Average across all values	0,93	1,87
Average without outliers	0,79	1,11

Table 2: Meta-analysis of the ratios between SDE/TT and SDL/TT (Börjesson, 2009).

3.6 Target sample

Defining the target sample is often equally important to building the stated choice experiment itself, since the design is often tailored for the target sample. In our case we defined our target sample as individuals who commute to work in the morning rush hour driving a car. A key concern in the design phase was how to deal with individuals who (already) have a preferred arrival time at the edge of the morning commute rush hour, hence they avoid (some of the) congestion while arriving at their PAT, i.e. no rescheduling delay. The tricky part – especially when presenting both an earlier and later departure time option – is to maintain realism among the alternatives presented to the respondents, while still offering alternatives which are not dominated by their current departure time. In order to limit the skewness in realism we decided to narrow the time interval of interest until the travel time distribution can be considered (somewhat) uniform. However, in the end we loosened this restriction slightly in order to increase the potential sample population. Ultimately, we defined our target sample as individuals who:

- Commute to work by car
- Have a travel time between 10-60 minutes to work
- Experience congestion on the way to work (i.e. traveling towards the city center)
- Arrive at work between 7:00-9:00 AM
- Are between 18-65 years

The choice of focusing on morning commuting trips to work towards the city center is quite typical in the studies on departure time given the distinct peak in demand for travel (Fosgerau & Karlström, 2010) and is motivated by the fact that Copenhagen (like most modern cities) faces severe congestion problem (The Forum of Municipalities, 2008), especially in the morning rush hours. The upper and lower TT boundaries were defined 1) in order to ensure that the travel time was not too short, otherwise there would be little incentive for the respondent to consider rescheduling, and 2) because appr. 95% of all commuting trips by car in the Danish National transport survey had travel time duration of less than 60 minutes during the morning peak period in the greater Copenhagen area, thus nearly all trips would be covered by this interval. Finally, as mentioned in the beginning, we predefined a set of groups to which respondents were assigned to the group who were closest to their own travel characteristic. In our case we predefined groups with travel time intervals of 10 minutes, hence we defined six different groups of TT=10,20,30,40,50, and 60 minutes. Based on these predefined groups, we built six different efficient designs accordingly.

4 Balancing the design

Once the alternatives, attributes, levels and the prior parameters have been defined we can start building the design. The design is constructed through an iterative process which follows the following steps:

0. **Define initial starting values:** the levels and priors are defined (discussed in section 3).
1. **Generate design:** this process built the experimental design
2. **Simulate choices:** this process creates hypothetical choice sets, which is used to test the design
3. **Estimate parameters:** based on the synthetic datasets we estimate the model parameters
4. **Evaluate performance:** finally, the estimated parameters are compared to the prior parameters
 - a. If design meets requirement (e.g. prior parameter can be recuperated), then stop.
 - b. Else, adjust the levels and/or the prior parameters and go to step 1.

To **generate** the design we used the software package Ngene (ChoiceMetrics, 2012). We constructed a D-efficient design using a RSC (Relabeling, Swapping and Cycling) algorithm¹. Since we are using non-zero priors we compute the *D-error* as follows (Rose & Bliemer, 2009):

$$D_p \text{ error} = \det(\Omega_1(X, \hat{\beta}))^{1/K} \quad (9)$$

Where Ω_1 is the asymptotic variance covariance matrix of dimension $K \times K$ as a function of the experimental design, X , and the prior parameters, $\hat{\beta}$, while K is the number of parameters. A small *D-error*, denotes an efficient design. We ran the software until no noteworthy improvement occurred for the *D-error*. This was done for all six designs (TT=10-60min). Afterwards, we **simulated** the choice by calculating the systematic utility using the prior parameters, and drawing identical and independently distributed (i.i.d.) random error terms from an extreme value (EV) type 1 distribution. The alternative with the highest probability was chosen. The design was simulated using appr. 18,000 observations. We then **estimated** the parameters using the simulated choices. The estimation was done using using PythonBiogeme (Bierlaire, 2003; Bierlaire & Fethiarison, 2009). Finally, when **evaluating** the design, we calculated the ratio and t-test for the estimated parameters against the prior parameters. Furthermore we verified that the micro-economic conditions are fulfilled and that $0 > \beta_{SDE} > \beta_{SDL}$, which according to previous studies should be expected. After testing a wide range of designs and numerous adjustments a final design was reached in which the true parameters could be recuperated and the size and magnitude were as expected. Table 3 shows the evaluation of the final designs against the priors, while table 4 shows the level values used in the designs.

Parameter	Coeff. Estimate	Std. error	t-stat	Scaled parameters ²	Prior parameters	$\hat{\beta}/\beta$	t-test against β
β_{ETT}	-0.011	0.003	-3.760	-0.009	-0.012	1.341	1.005
β_{TC}	-0.017	0.003	-5.120	-0.014	-0.018	1.312	1.245
β_{ESDE}	-0.013	0.002	-7.720	-0.010	-0.008	0.795	-1.232
β_{ESDL}	-0.015	0.002	-9.400	-0.011	-0.012	1.080	0.583

Table 3: Evaluation of the final designs against the priors.

Attribute	Unit	Levels			
		1	2	3	4
Departure time change - early	[min]	-15	-30	-45	
Departure time change - late	[min]	15	30	45	
TT - early & late	[%]	70	80	90	
TTV - TT 10 & 20 min	[min]	3	6	9	
TTV - TT 30 & 40 min	[min]	5	10	15	
TTV - TT 50 & 60 min	[min]	10	20	30	
TC - current	[DKK]	16	19	22	25
TC - early & late	[DKK]	7	10	13	16

Table 4: Level values used in the final design.

¹ The RSC-algorithm was applied using the following settings: swap(random=500, swap=1, swaponimprov=40, reset=10000, resetinc=5000)

² The synthetic dataset were generated assuming a scale of 1.28 in the error term.

5 Questionnaire

After finalizing the SP design, we needed to construct the remaining of the questionnaire. For that we relied on a heavily modified version of the Danish National Transport Survey (TU) (Christiansen, 2012; Christiansen & Skougaard, 2013). This was decided in order to utilize the experienced gained through collecting data in a Danish context. The questionnaire built for this study was structured in six phases:

- 1) **Introduction and some initial questions.** After a brief introduction on the scope of the study, respondents were presented with some questions (in particular their preferred arrival time and their home and work location) which allows us to customize the remaining of the questionnaire.
- 2) **Full trip/activity diary.** Respondents were then asked to describe the trips performed during their last working day. This part of the survey was based on the TU survey trip diary (Christiansen, 2012) that contains detailed information on all trips and activities (also the ones with very short duration), such as transport mode, departure time, travel time, and purpose of the trip, and if the trip was performed alone or jointly with other people.
- 3) **Flexibility of each trip reported in the diary.** In addition to the traditional (in the departure time studies) information about fixed/flexible working hours, we also included a set of highly specific question to specifically capture the flexibility constraints for each trip in the trip diary. These questions aimed to capture potential (often not conscious) constraints in the departure time that are not revealed by the typical question whether the work is flexible or not.
- 4) **Stated preference experiments.** Based on the information reported in phase 1 and 2, a customized Stated Preference (SP) experiment was presented, where individuals were asked to choose among three departure times: the current departure time and an earlier or later departure time, see figure 1.
- 5) **Indicators for latent constructs.** A set of 24 statements (ranked on a 1-5 likert scale) were used to define 8 latent constructs according to the theory of the planned behavior (Ajzen, 1991). The latent constructs are *Intention*, *Attitude* (towards short travel time, being flexibility, and being on time), *Social Norm* (SN), *Personal Norm* (PN), *Perceived Behavioral Control* (PBC), and *Perceived Mobility Necessities* (PMN). For more information see Haustein et al. (2014).
- 6) **Socio-demographic information** about the respondent and her/his family. For all the household members we collected: age, sex, income, household position (e.g. father/mother), and if they have a driving license. For the person interviewed we also collected: level of education, occupation, work location, if they have bike and/or season ticket, parking facilities at work, possibility to work from home (number of days within the last month), working hours per week and whether these are fixed or flexible. Finally, we collected a few household characteristics: household location, household composition, parking facilities at the household, and number of cars in the household.

It is important to note that the SP exercise was presented within the trip diary; i.e. as soon as a work trip was registered in the trip diary the respondent was presented with the SP choice experiment for that specific trip. The questionnaire was designed in this way in order to present the choice situation as early as possible in order to make sure that the respondent still has the actual trip and – more importantly – the actual constraints fresh in mind. After having completed the SP, respondents were asked to continue the trip diary.

The questionnaire was designed as an online survey. The main advantages of using a web based questionnaire is that 1) it allows to easily constructing customized questionnaires (which is important due to realism) with conditional questions for each respondent based on their specific trips and socio-economic characteristics, 2) the cost per interview is relatively small, which allows for a larger sample size with limited resources, 3) it allows to define a set of criteria to be fulfilled by the people within the internet panel, and in that way ensure that only people who is in our target sample is present in the final sample, and 4) it allows respondents to answer the questionnaire when they have time, thus a higher answer-rate. The disadvantage is that some groups of society (who do not use computers, e.g. kids and elderly people) are not present in the survey. However, since this study is limited to work trips in the rush hours, neither kids nor elderly people will be in the target group.

Valgsituation 1 ud af 9

Hvad vælger du ?

	Rejse A	Rejse B	Rejse C
Afrejsetidspunkt	08:00	07:30	07:00
Rejsetid	4 ud af 5 gange tager rejsen 24 minutter (ankomst 08:24) 1 ud af 5 gange tager rejsen 39 minutter (ankomst 08:39)	4 ud af 5 gange tager rejsen 30 minutter (ankomst 08:00) 1 ud af 5 gange tager rejsen 45 minutter (ankomst 08:15)	4 ud af 5 gange tager rejsen 21 minutter (ankomst 07:21) 1 ud af 5 gange tager rejsen 31 minutter (ankomst 07:31)
Pris	10 kroner	16 kroner	16 kroner
Dit valg ?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

<- Tilbage / vis forrige Godkend / Videre ->

Figure 1: example of a choice task for a respondent with preferred arrival time 9:00.

6 Discussion & concluding remarks

For this study we designed an efficient design for departure time for morning car commuters with three departure time alternatives: an early and late departure time option, and a departure time which are close to their current. The two most challenging aspects of generating stated choice experiments for departure time choices are 1) obtaining realism, and 2) dealing with interdependencies among attributes. To ensure realism we used a pivot design using their current travel times as a reference. It can however be argued that using the TT reported by the respondents is not ideal, since individuals often have a tendency to overestimate the time spend travelling. However two main steps are believed to minimize such effect. Firstly, a control feature was built into the questionnaire, comparing length travelled with the reported time, thus prompting the respondent to verify or reconsider the reported travel time if the average speed was found to be unrealistic. Secondly, since we wanted to perform a 1-step data collection, we pre-defined six groups with specific travel characteristics ranging from TT=10-60 minutes with 10 minutes intervals between the groups. The respondents were then assigned to the group to which they were closest, thus the reported TT of the respondents were not used directly to generate the designs. The interdependencies among variables was dealt with by carefully selecting the level values, thus ensure that rescheduling would reduce TT, while at the same time defined an interval of interested during the morning rush hours for the target group, thus ensuring that the respondent was actually facing congestion in their current departure time slot. We defined that respondent should currently arrive at work between 7:00-9:00 AM, and travel towards the city center.

The benefit of building an efficient design is that the experimental design is tailored specifically to the model specification, and thus improving the parameters estimation. The downside is that the design is less flexible in cases where the model specification and true parameters are not known or little information available about the true parameters. However, for departure time choices the scheduling model have almost become the standard approach, hence a number of studies were available to hint about the true parameter. It is difficult to say if the efficient design performs better than a similar orthogonal design would have taking into account the additional time and effort needed to create the efficient design. However, we note that overall we managed to construct an efficient design, and recuperate the prior parameters. The t-tests of the estimated parameters were not statistically different from the prior parameters at 95% confidence.

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HOW FLEXIBLE IS FLEXIBLE? ACCOUNTING FOR THE EFFECT OF RESCHEDULING POSSIBILITIES IN CHOICE OF DEPARTURE TIME FOR WORK TRIPS

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Abstract

In departure time studies it is crucial to ascertain whether or not individuals are flexible in their choices. Previous studies have found that individuals with flexible work times have a lower value of time for late arrivals. Flexibility is usually measured in terms of flexible work hour start time or in terms of constraints in arrival time at work. Although used for the same purpose, these two questions might convey different types of information. Moreover, constraints in departure time are often related not only to the main work activity, but to all the daily activities. The objective of this paper is to investigate the effect of constraints in work and in other daily trips/activities, on the willingness to shift departure time and the willingness to pay for reducing travel time and travel delay. A dataset was specifically collected to have details on the full 24-hour out-of-home activities, and on the constraints for each of these activities. A stated preference experiment was built to infer preferences on departure time choice, and a mixed logit model, based on the scheduling model, was estimated to account for the effects of daily activity schedule and their constraints. Our results clearly show that measuring flexibility in terms of start working hours or constraints at work do not provide exactly the same information. In particular one third of the workers with flexible working hours in our sample declared that they do have constraints and only the information on constraints at work allows us to reveal differences in preferences for scheduling delay late. This leads to different conclusion in terms of demand sensitivity to scheduling delay late. We also found that having other activities and constraints during the day increases the individuals' willingness to pay to avoid being late at work, where the presence of constraints on daily activities other than work is particularly relevant for individuals with no constraints at work. The important impact of these findings is that if we neglect the presence of constraints, as is common practise in transport models, it will generally lead to biased value-of-time estimates. Results clearly show that the shift in the departure time, especially toward a late departure time, is strongly overestimated (the predicted shift is more than double) when the effect of *other* activities and their constraints is not accounted for.

Keywords: Departure time, scheduling model, flexibility constraints, activity schedule

1 Introduction

Urban congestion represents “*one of the most relevant preoccupations of transport specialists both in the developed and developing world*” (Ortúzar et al., 2014, pp. 691). Among the various travel dimensions that play a role in travel congestion, departure time is one of the most important. A number of studies have shown that people are more likely to change their departure time to address the problem of congestion rather than changing mode (Hendrickson and Planke, 1984; Kroes et al., 1996; Hess et al., 2007a), and are even less likely to change their work and residential location. Departure time choice is typically modelled by using the scheduling model (SM) formulated by Small (1982) and based on the bottleneck theory (Vickrey, 1969; Coslett, 1977). The basic concept is that individuals have a well-defined preferred arrival time (Day et al., 2010), and they will trade travel time and (early or late) scheduling delays (i.e. difference between the preferred and the actual arrival time) in order to avoid congestion. If a traveller arrives at a preferred arrival time the (penalty from) scheduling delay will equal zero. The SM was later extended to include travel cost (Small, 1987), a discrete lateness penalty to specifically capture the impact of late arrival (Noland and Small, 1995) and travel time (un)reliability (Small et al., 1995; Noland and Small, 1995; Noland et al., 1998; Small et al., 2000; Small and Lam, 2001; Ettema et al., 2004b; Tseng et al., 2005; Börjesson, 2007; Börjesson, 2008; Börjesson, 2009; Tseng et al., 2011; Börjesson et al., 2012; Koster and Verhoef, 2012). Recently Fosgerau and Karlström (2010) derived a simplified form of the linear scheduling model. They proved that the mean-varian model is theoretically equivalent to the scheduling model, but Börjesson et al. (2012) did not find the equivalent in empirical data.

Crucial in the departure time is whether individuals are flexible or not in their choice. If people are completely flexible, they can change their departure time freely and there should be no restrictions on their substitution pattern. In this case demand elasticity is expected to be high. If on the other hand people are inflexible (or are restricted in their flexibility), their substitution between choices is limited and their elasticity should be low. This has been recognised since the early studies on departure time, though discussion mainly focused on the analysis of the estimates and value of time, not on the effect on demand elasticity. Small (1982) used revealed preference (RP) data consisting of commuting trips to work, where respondents were asked how late they could be, with respect to the working hours start, without it mattering much. He found that people who are flexible have a lower value of time of late arrival, both for scheduling delay late and discrete lateness dummy. Hendrickson and Planke (1984) accounted for flexibility by imposing zero scheduling delay for all commuters with flexible working hours. For individuals with fixed working hours, they found a significant and positive squared terms for both scheduling delays, both early (SDE) and late (SDL), indicating that the marginal disutility of being delayed decreases as the delays increases. Similar results were found in Polak and Jones (1994). Mannering (1989), which accounted for flexibility in commuting trips by including a dummy indicator for people with flexible working hours, found that they change departure time more frequently, albeit the statistical significance of the parameter is relatively low. He argued that this is probably due to a “broad” rush hour, which yields little benefit in rescheduling (he uses RP-data). De Jong et al. (2003) estimated different scheduling delays for commuters using cars or the train with flexible and fixed working hours and commented that the value of time for early and late arrival was higher for inflexible than for flexible individuals. Börjesson (2007; 2008; 2009) and Kristoffersen (2013) used data collected in Stockholm where respondents were asked about the latest possible arrival time at work, and comparing this with the actual trip, they classified individuals as fixed and flexible. They estimated separate models for 1) flexible commuters and other trips, 2) fixed commuters and school trips, and 3) business trips. They commented that for commuters with a fixed schedule both late arrival and early departure are more costly than in other model segments. Börjesson et al. (2012) had information about constraints at origin/destination for public transportation commuters, and found little or no difference between people with and without constraints. They commented that most individuals have constraints to some extent, but these are rarely absolutely “binding”. Arellana et al. (2012) collected information about official start/end working hours and whether these times were flexible or not (schedule flexibility) but they did not explicitly report different analyses for these categories. Finally, Lizana et al. (2013) distinguished between high and low flexibility depending on whether respondents can arrive at work

more than 30 minutes late with respect to their official work starting hours and found that highly flexible people value less arriving late at work, while Asensio and Matas (2008) used the same definition but with a threshold of 10 minutes.

The effect of flexibility in departure time studies has typically been measured in terms of flexible or fixed start/end working hours, or in terms of constraints with respect to arrival time at work. Although these two questions are used for the same purpose in departure time models, we envisage that they might not convey exactly the same type of information. The problem can be semantic, because the wording of the question typically affects the way people understand and hence answer questions. However, having fixed working hours does not necessarily imply that people are not allowed a certain degree of flexibility in how early or late they can arrive at work and vice versa. Moreover, the information about fixed/flexible working hours measures general working conditions, while the information on constraints can vary from day to day and it is more related to the specific trip. In this sense, beyond the importance of the wording, the two sets of information can reveal varying effects. Since flexibility at work is a crucial issue in departure time studies, we believe it is important to explore the extent to which the way the question about flexibility is asked, will reveal different effects, and to which extent this has a policy implication.

Common for the studies discussed above, is that they only account for constraints at the work location, assuming that (different types of occupations at) work is the main source of heterogeneity in departure time flexibility (Hall, 2013). However, constraints that can affect departure time often go beyond flexibility of working hours. Some studies have incorporated the link between both legs of the tour with main-purpose work, by modelling the joint decision between the outward and return legs of the same tour (Polak and Jones, 1994; de Jong et al., 2003; Ettema et al., 2004a; Hess et al., 2007a; Hess et al., 2007b; Arellana et al., 2012). This implicitly includes the activity participation time of the main activity (i.e. work time) because the link between both tour legs of the tour depends on the duration of the activity performed at the tour destination (de Jong et al., 2003). Following the work of Polak and Jones (1994) on the joint choice of departure time and activity time, de Jong et al. (2003) recognised that restrictions on the departure time can also be imposed by time spent participating in other daily activity. But they account for that estimating two variables that measure the penalty for decreased and increased work time. This same approach was used by Hess et al. (2007a; 2007b) who also added an error component to investigate the effect of unobservable influences in time-of-day switching. They found that commuters generally have a greater sensitivity of shifts to later departure times compared to earlier ones. Additionally, travellers are generally less sensitive to changes in participation time than they are to changes in departure time. Later, Arellana et al. (2012) also adopted this approach, and they found that people are more worried about meeting schedules in the morning but they did not find significant differences between value of time estimated with trip, tour and joint trip-tour models, and state that these findings should be treated with caution.

The above studies focus on tours to work and time spent working, but do not analyse the effect of the daily activity schedule (i.e. no-work activities) on the departure time preferences for the work trip. As well-recognised in the activity-based literature (e.g. see Bowman and Ben-Akiva, 2000) the choice of when to realize a given trip is (often) related to the full daily activity schedule. Since time/space constraints in one activity may form restrictions in the flexibility of other activities, these affect the preference for the related departure time (Jenelius, 2012). Arellana et al. (2012) highlighted that the performance of other activities during the day could impose restrictions on departure time choices, but they did not include this effect in the model. Lizana et al. (2013) modelled specifically the number of intermediate stops made to drop or pick someone up on the way to work, but mainly to account for the higher flexibility of the car compared to the bus, as they estimated a joint mode-departure time model. Asensio and Matas (2008) mentioned that they tested the effect of specific activities (such as shopping or taking children to school) on the preference for time and variability but they did not find significant results. So they only reported a model where they differentiated between commuters who can start working at any time and those that have fixed starting hours.

From this literature it is clear that the effect of other activities on the departure time to work is considered an important research question. However, no studies provide evidence of the effect that daily activities and their

constraints have on the choice of departure time to work. In this research we aim to fill this gap. The overall purpose of this research is to explore whether, and to which extent, the willingness to shift (WTS) departure time to avoid congestion and willingness to pay (WTP) in order to reduce travel time and travel delay to work are affected by the way information on flexibility at work is collected, and by other trips/activities carried out during the day, and whether they have constraints. We also provide empirical evidence of the policy implication in terms of their impact in the shift of the demand predicted. The working hypotheses that we will test are that: (1) the current ways of measuring flexibility might allow us to capture different effects; (2) other activities carried out during the day affect the WTS and WTP for the working trips, especially for individual with flexible work times and (3) constraints on other activities would cause the WTP to increase as it represents an extra cost. Understanding and quantifying the effect of flexibility is an important contribution. It is of particular relevance when assessing transport policies, to avoid overestimating demand elasticity and thus the shift predicted in response to crucial intervention such the implementation of congestion pricing schemes.

To achieve this goal a survey was specifically designed for this study to gather information on the respondents daily out-of-home activity/trip pattern and in particular on the degree of flexibility of each activity/trip. Data on the departure time choice was collected using a stated preference survey and a full D-efficient design. To measure flexibility in individual activity schedule, a set of specific questions was asked for each trip performed during the day, aiming at discovering whether the trip (and the related activity) was constrained in space, time or due to interaction with other people. It is also important to highlight that (especially in habitual trips) people often tend to make decisions without thinking about the real constraints motivating that decision. Hence, these questions were also designed with the aim to make people think and thus reveal the true constraints that might affect their departure choice. A departure time model was estimated which accounts for the effect of the activity schedule and the constraints. We used the discrete approach based on the scheduling model because in stated preference data the choices are built as discrete departure time choices, and we used the mixed logit specification to account for the panel effect due to the repeated observations from the same individual. Although the departure time is continuous by nature, the discrete approach offers the theoretical advantage of being consistent with the microeconomic theory, and the benefits measures derived from that (see for example Lemp et al., 2012).

The paper is organized as follows: Section 2 describes the survey methodology, Section 3 reports a descriptive analysis of the sample and its characteristics. Section 4 describes the model specification while Section 5 reports the discussion of the results obtained. Section 6 summarizes our conclusions.

2 Data collection

Data was collected specifically for this research with the focus on the departure time of workers who live in the suburbs and work in the city centre of the metropolitan area of Copenhagen. The decision to focus on morning commuting trips to work by car towards the city centre is quite typical in the studies on departure time given the distinct peak in demand for travel (Fosgerau and Karlström, 2010) and is motivated by the fact that Copenhagen, like most modern cities, faces severe congestion problems (The Forum of Municipalities, 2008), especially in the morning rush hour.

The sample was collected at different locations and through two main sources. Initially, respondents were recruited through an internet panel. But we had a very low response-rate, which is unusual for internet panels. Thus, we decided to contact individuals directly at their work place. Two universities (University of Copenhagen and Copenhagen Business School) and three companies and public organisations – among the biggest ones located in the central Copenhagen were selected. These five locations were chosen based on the number of workers (they total over 16,500 workers), their location in the city (they cover the relevant destinations very well) and based on the type of job (they guarantee heterogeneity in terms of job type). In collecting samples at destination it is common to select the venues for interviewing people strategically,

without necessarily being representative of the population (see for example the Santiago panel as described in Yáñez et al., 2010).

At the companies, the public departments and at the Universities all employees were invited to participate. More than 10,000 invitations were distributed by email and we received 923 fully completed questionnaires. Among these, 437 were from respondents who did not own a vehicle or did not use it to go to work. The remaining data was ‘cleaned’ based on a few criteria. In particular, we excluded individuals who, during their most recent working day before the interview, did not arrive at their workplace between 6:00 to 10:00, and had a travel time to work (by car) between 10-65 minutes. According to the Danish National Transport survey (Christiansen, 2012), less than 8% of the individuals travelling by car into Copenhagen in the peak morning have a trip shorter than 10 minutes and only 7% have a trip longer than 65 minutes. After ‘cleaning’ the data, the final sample available for the model estimation consisted of 286 respondents.

The sample was collected using a web-based questionnaire¹ as it allows for 1) constructing customized questionnaires (which is important to guarantee realistic scenarios) with conditional questions for each respondent based on their specific trips and socio-economic characteristics, 2) gathering larger samples at relatively low cost per interview, and 3) using criteria to define the target sample. In today’s society very few people do not use (or have access to) a computer, so the risk of biased samples was limited. The questionnaire was structured in the following six phases:

- 1) **Introduction and some initial questions.** After a brief introduction on the scope of the study, respondents were presented with some questions, in particular their preferred arrival time (PAT) and their home and work location, which allowed us to customize the remainder of the questionnaire.
- 2) **Full trip/activity diary.** Respondents were then asked to describe the trips performed during their most recent working day. This part of the survey was based on the Danish National Transport survey that contains detailed information on all trips and activities (also the ones of a very short duration), such as transport mode, departure time, travel time, and purpose of the trip, and if the trip was performed alone or jointly with other people.
- 3) **Flexibility of each trip reported in the diary.** In addition to the traditional (in the departure time studies) information about fixed/flexible working hours, a set of detailed questions was included to capture the constraints for each trip in the trip diary.
- 4) **Stated preference experiments.** A Stated Preference (SP) experiment was customized, based on the home-to-work trip, as described by each individual in phases 1 and 2 of the questionnaire. Individuals were asked to choose from three departure times for the trip from home to work: the current departure time as well as an earlier and later departure time.
- 5) **Indicators for latent constructs.** A set of 24 statements (ranked on a 1-5 Likert scale) were used to define 8 latent constructs according to the theory of the planned behaviour. More details on the latent indicators can be found in Thorhauge et al. (2015).
- 6) **Socio-demographic information** about the respondent and his/her family. For all the household members the following socio-economic information was collected: age, sex, income, role within the family (e.g. parent/child), and if they held a driver’s license. We also collected information from the interviewees on: level of education, occupation, work location, if they had bicycle and/or season ticket, parking facilities at work, possibility of working from home (number of days within the last month), working hours per week and if they had fixed or flexible start/end hours working. Finally, a few household characteristics were also collected such as: municipality of household residence, parking

¹ The questionnaire is in Danish and it is available upon request. The authors will make their best to provide any possible clarification for non-Danish speakers.

facilities at the residence place, and number of cars at the household. This part was also based on the Danish National Transport survey.

The SP was presented as soon as a work trip was registered in the trip diary in order to ensure that respondents still had the actual trip and more importantly the actual constraints fresh in their mind. After having completed the SP experiment, respondents were asked to continue to complete the trip diary.

2.1 Efficient design for departure time choices

The SP experiment was built using a D-efficient design where individuals were asked to choose between three alternative departure times: the current departure time, an earlier and a later departure time. The major benefit of an efficient design is that higher efficiency is obtained with a smaller sample size (Rose and Bliemer, 2009). In particular the D-efficient measure aims at minimize the determinant of the asymptotic variance-covariance matrix. Whatever efficient measure is used, building an efficient design for the departure time is challenging because attributes are interdependent and the design attributes presented to the respondents differ from those in the model, by which the design is created (Koster and Tseng, 2009). In fact, Arellana et al. (2012) are the only ones to use an efficient design for departure time studies, but they built a two-step optimized design, which breaks the efficiency. We overcame this problem pivoting the travel time around the preferred arrival time instead of around the actual departure time. We verified that the difference between the two approaches is equal to a constant k , which can be controlled by defining narrow threshold values for rush hours, and ensuring that the preferred arrival time and the actual trip occurs during rush hours (Thorhauge *et al.*, 2014). As mentioned in Section 2, we carefully selected our sample to include only people who actually went to work within the rush hours.

An implicit scenario was assumed, and before presenting the SP options, individuals were informed that a congestion price scheme had been implemented and that they had to pay a toll for their current departure time. The Copenhagen municipality has been discussing for quite some time the introduction of a toll to enter the city, so individuals are familiar with this type of scenario and certainly perceived it as realistic.

SP options were customized based on the trips described by each individual in the trip diary and based on the departure time needed in order to be at work at their preferred arrival time (as reported in phase 1 of the questionnaire). It is important to note that customizing the experiment specifically for each individual is not possible with efficient designs, unless the real trips are known before optimizing the SP design (which in any case requires optimizing as many designs as individuals). In order to adjust the design to the characteristics of the individuals' trips, travel times were classified into six classes: 10, 20, 30, 40, 50, and 60 minutes (based on the distribution of trip lengths in Danish National Transport survey). Based on the predefined classes of possible travel times, six different designs were then constructed and respondents were presented with the design that was closest to their travel time as reported in the trip diary.

The attributes included in the SP experiments are departure time (DT), travel time (TT) and travel time variability (TTV) at 3 levels each, and travel cost (TC) at 4 levels. Following the approach in Arellana et al. (2012), the travel time variability was included as an unexpected delay once a week. Since TTV is not the main focus of our work, we decided on a more straightforward approach. In particular we defined the TTV as the TT that individuals experience once a week, hence with a probability of 20%.

For the prior parameters we relied on a meta-analysis reported in Börjesson (2009). The SP experiments were tested using simulated data (approximately 20,000 observations were generated following Williams and Ortúzar (1982)) and four pilot samples. The efficient design was constructed using the software package Ngene (ChoiceMetrics, 2012). A set of constraints was used to ensure that the relation between design attributes and model attributes (i.e. the relation between travel time and scheduling delays) was maintained. For each of the 6 predefined travel time groups an efficient design was generated with a total of 27 choice tasks which were divided into 3 random blocks, so that each respondent was presented with a total of 9 choice tasks.

2.2 Scheduling constraints

As mentioned in the introduction, a person might have flexible working hours, but be constrained due to other activities realised during the day. The extent to which other activities affect departure time to work depends on the degree of flexibility of the other daily activities. Following the typical literature in time geography (Hägerstrand, 1970) three types of constraints were considered in this study: temporal, spatial and social constraints. Additionally we also considered whether the activity could have been omitted (compulsory/essential) and the latest/earliest possible arrival/departure time. In particular the following set of questions was asked for each trip (even small intermediate trips):

- **Compulsory/essential activity:**
 1. Could you have omitted this trip/activity? (yes/no)
- **Activity constrained in space:**
 2. Could you have carried out this activity at another location? (yes/no).
- **Activity constrained in time:**
 3. Could you have done this activity another day? (yes/no)
 4. Could you have done this activity at another time of the day? (yes/no).
 5. Were there any restrictions to how early you could have departed? (yes/no) If “yes” what is the earliest possible departure time?
 6. Were there any restrictions to how late you could have arrived? (yes/no) If “yes” what is the latest possible arrival time?
- **Activity constrained due to the interrelation with other people (social constraints):**
 7. Could another person have done this activity for you? (yes/no)
 8. Did you decide yourself when to depart? (yes/partly/no)

The 8 above questions were conditional on the trip purpose. If the trip purpose was to return home only questions 5, 6, and 8 were asked, while if the trip purpose was going to the main work location, only questions 2, 5, 6, and 8 were asked. For example, though it is possible for people to return home from work another day of the week, we felt in most cases the question would have sounded rather awkward. For all other trips purposes all 8 questions were asked.

3 Sample characteristics

In this section we briefly describe the characteristics of the sample gathered, and analyse in detail the structure of the activity pattern and flexibility constraints as revealed by the data. We distinguish between “flexibility at work” and “flexibility on daily activities other than work”.

The data was collected in the autumn of 2013, and consists of individuals living in the Greater Copenhagen Area and working in the City Centre. The sample is aligned with the Danish National Transport survey, which is representative of the Danish population, for socio-economic characteristics such as gender and age but it is skewed toward high education, flexible working hours and number of working hours per week. This was expected because data was collected at universities and non-service industries, which also explains why income is slightly higher than the general average of Greater Copenhagen Area. However, and perhaps even more importantly, our sample is similar to the Danish National Transport survey in terms of average number of trips per respondent (3.13 in our sample and 3.21 in Danish National Transport survey) and tours (1.22 in our sample and 1.37 in Danish National Transport survey).

As discussed in the introduction, in departure time literature, two operational definitions of flexibility at work are used: (1) fixed/flexible start working hours and (2) the latest acceptable arrival time (i.e. constraints

in the arrival time). In our work we adopted both definitions because one of our goals is to compare these two types of information typically used to measure flexibility in arrival time at work.

An operational definition of flexibility in daily activities has never been used in departure time studies. Lizana et al. (2013) are the only people to test a measure of trip complexity, but referred only to a specific type of activity (i.e. dropping someone off) that implies also a social constraint. Scheiner (2014) reports a good review of the measures of complexity adopted in the literature. The *trip complexity* refers to the number of stops involved in a trip chain (defined as that part of tours that links two ‘anchors’, typically home and workplace) or in a tour (defined as a sequence of trip chains starting and ending at home). The *activity pattern complexity* is less straightforward as, other than the number of activities performed, it involves also the relative amount of time devoted to each activity. The Shannon’s entropy measure is often used in this case. These measures however do not consider the possible constraints on the activities and do not distinguish among type of activities performed. Both are relevant points in the departure time choice. Akar et al. (2012) consider the type of activities and their constraints, to study what makes people choose between groups of activities. They used a weekly activity diary that contains detailed information on the duration of the activities, their planning horizon, whether performed with someone else, the type of activities performed at home, and whether each activity was constrained or not. Though they have a detailed list of activities, they mainly focus on the distinction between work and leisure activities and between in-home and out-of-home activities. They find that out-of-home activities tend to be either constrained in both time and space, or flexible in both dimensions. Activities performed with others (social constraints) tend to be flexible in both time and space.

Based on this literature, we tested flexibility in daily activities in terms of (1) number of intermediate stops (i.e. stops for purposes other than work and business) in the main tour around work and (2) distribution of stops within trip chains. The number of stops in a tour measures how efficiently individuals organise their trips; it is expected that the more complex the tour around work, the more efficient the organisation will be, and the higher the disutility of rescheduling. The distribution of stops measures the amount of heterogeneity in the distribution of the stops for other purposes across the trip chains. It is expected that the more scattered the activities along the tour the more individuals would prefer an earlier departure in order to be able to fulfill all their daily plans. For this second measure we used the Shannon’s entropy measure ($H = -\sum_t p_t \ln(p_t)$) where p is the percentage of stops realized in each trip chain t . $H = 0$ means that all stops (i.e. other activities) are concentrated only in a trip chain, $H > 0$ means that activities are spread across different trip chains during the main tour around work. We defined the trip chains as follows:

- 1) **Before Work (BW)**, if the (sequence of) activities/trips is part of a home-based tours realised before going to work. These activities in our sample are carried out in the morning.
- 2) **Between Home and Work (WH)**, if the (sequence of) activities/trips is realised on the way from home to work. These activities - in our sample - are carried out in the morning.
- 3) **Around Work (WW)**, if the (sequence of) activities/trips is part of a work-based tours. These activities - in our sample - are carried out during the day.
- 4) **Between Work and Home (WH)**, i.e. the sequence of activities/trips realised on the way back from work to home. These activities in our sample are carried out in the evening.
- 5) **After Work (AW)**, i.e. the sequence of activities/trips is a home-based tours realised after returning home from work. These activities in our sample are carried out in the evening.

In line with the literature and the way data was collected, we tested 3 types of constraints: temporal spatial and social constraints. We performed a principal component analysis based on the type of activity, trip chain and the type of constraints. However, these aggregated measures cannot be used to disentangle the disaggregate effect of specific activities relating to trip chain and constraints.

3.1 Flexibility at work

Table 1 shows the comparison between having fixed/flexible working hours and having constraints in the arrival time (i.e. if individuals have any constraints in arriving later at work). Firstly, we note that 65% of our sample is formed by individuals with flexible working hours (35% with fixed working hours), while 51% declared that they have no constraints in their arrival time to work. More interestingly 30% of the workers with flexible working hours declared that they do have constraints with arriving later; while 16% of the workers with fixed working hours declared they had no constraints in arriving later. This is in line with our assumption that the two operational measures of flexibility at work do not measure exactly the same phenomenon.

Constraints in how late individuals can arrive at work	Individuals with flexible start/end working hours	Individuals with fixed start/end working hours	Total
No Constraints	45.50%	5.70%	51.20%
Constraints	19.70%	29.10%	48.80%
Total	65.20%	34.80%	100.00%

Table 1: Trips to Main Work destination

Table 2 reports the types and distribution of tours in our sample. The 27 trip purposes reported in the trip diary were divided into 5 groups: home (H), main work location and business (WB), escort, errand, leisure, and education (also indicated as *other* purposes “Ot”). As expected the majority of the sample (80%) has only one home-based tour around work and in half of the cases (44%) it is a simple tour without intermediate stops; 36% of the sample has only one tour but with other activities (than work). Among the individuals who performed some activity other than work, the majority has other activities only on the way home from work or after returning home. Individuals with flexible working hours are more likely to perform only one tour but more complex (i.e. with activities other than only work) than individuals with fixed working hours. Individuals with no constraints have a similar pattern, but they have more simple tours without intermediate stops than individuals with constraints.

Tour types	Distribution of tour types	Start/end working hours		Constraints in how late individuals can arrive at work	
		Flexible	Fixed	No Constraints	Constraints
1 tour	80.07%	82.26%	73.96%	84.03%	75.35%
H-WB-H	43.71%	41.94%	46.88%	44.44%	42.96%
H-WB-Ot-H	20.98%	23.12%	16.67%	21.53%	20.42%
H-Ot-WB-H	5.59%	5.38%	6.25%	6.25%	4.93%
H-Ot-WB-Ot-H	6.64%	9.68%	1.04%	9.03%	4.23%
<i>Other types</i>	2.80%	2.15%	3.13%	2.78%	2.82%
2 tours	18.88%	16.13%	25.00%	14.58%	23.24%
H-WB-H + H-Ot-H	10.84%	10.22%	12.50%	9.03%	12.68%
H-WB-Ot-H + H-Ot-H	3.15%	2.15%	5.21%	1.39%	4.93%
H-Ot-WB-Ot-H + H-Ot-H	1.40%	1.61%	1.04%	0.69%	2.11%
<i>Others types</i>	3.50%	2.15%	6.25%	3.47%	3.52%
3 or more tours	1.40%	1.61%	1.04%	1.39%	1.41%

Table 2: Sample distribution of tours

Table 3 reports the analysis by trip chain. This analysis shows that non-work, out-of-home activities are mostly concentrated only in one trip chain: 47% of the activities for other purposes are realised in the trip chain between work and home (WH), 28% after coming back from work (AW) and 20% in the trip chain between home and work (HW). Individuals with flexible working hours or no constraints in how late they

can arrive at work have more trips for other purposes on the trip chains within the main tour around work, while individuals with fixed working hours or constraints have more trips for other purposes on the trip chains after coming back home from work.

Trip chains	Distribution of trip chains	Start/end working hours		Constraints in how late individuals can arrive at work	
		Flexible	Fixed	No Constraints	Yes Constraints
BW (H → H, <i>before work</i>)	4.52%	3.62%	6.66%	5.10%	3.96%
HW (H → WB)	20.10%	22.46%	15.00%	23.47%	16.83%
WW (WB → WB)	0.50%	0.73%	0.00%	0.00%	0.99%
WH (WB → H)	47.24%	49.28%	41.67%	48.98%	45.55%
AW (H → H, <i>after work</i>)	27.64%	23.91%	36.67%	22.45%	32.67%

Table 3: Sample distribution of trip chains including other trips than work/business

3.2 Flexibility on daily activities other than work

In this section we analyse the daily activities realised for other purposes (i.e. different from work/business and coming back home) and their temporal, spatial and social constraints. Table 4 reports for each type of tour, the average number of stops for other purposes (*trip complexity*). Table 5 reports the same analyses by trip chain. Table 4 reveals a clear pattern of activities where individuals who perform only one tour a day around work, mainly have escorting activities. Errands and leisure activities are instead mainly performed in the second or third tour of the day. The analysis by trip chain (Table 5) confirms that almost all the stops on the way between home and work are made to escort someone, while leisure and errands activities (accounting for 54% of the other activities in the day) are realised almost exclusively after work, either on the way from work to home (especially errands), or after having returned home from work (mainly leisure). Only one individual had stops for other purposes (escorting) during the sub-tour from work.

Tour types	Average number of other activities	Distribution among purposes			
		Education	Escort	Errand	Leisure
1 tour	0.63	1%	52%	31%	16%
Ho-WB-Ot-Ho	1.27	1%	26%	47%	25%
Ho-Ot-WB-Ho	1.13	0%	94%	0%	6%
Ho-Ot-WB-Ot-Ho	2.58	0%	77%	19%	5%
<i>Others types</i>		0%	71%	14%	14%
2 tours	1.50	3%	34%	20%	44%
Ho-WB-Ho + Ho-Ot-Ho	1.00	3%	7%	30%	60%
Ho-WB-Ot-Ho + Ho-Ot-Ho	2.44	0%	31%	25%	44%
Ho-Ot-WB-Ot-Ho + Ho-Ot-Ho	3.50	7%	64%	0%	29%
<i>Others types</i>	1.40	0%	55%	15%	30%
3 or more tours	2.25	0%	33%	11%	56%

Table 4: Average numbers of activities/trips and distribution by purposes.

The average number of stops for other purposes (escorting, errands, leisure or education) in complex tours around work (i.e. with at least 1 stop for other purposes in the main working tour from home to home) is 1.48. As expected it increases with the number and the complexity of the tours but it is evenly distributed across trip chains. The average number of stops in the main tour to work is higher for flexible people than for inflexible people and there is little difference between individuals with fixed working hours and individuals with constraints at work (and between individuals with flexible working hours and individuals with no

constraints at work). The Shannon's entropy for our sample is on average 0.134. This values is closer to zero than to the maximum value of 1.09, which confirms that activities for other purposes tend to be concentrated in few trip chains. The entropy values refer to the activities realized during the main tour around work. We found that individuals with flexible working hours have higher entropy (0.174) than individual with fixed working hours (0.023); analogously individuals with no constraints on how late they can arrive at work have higher entropy (0.165) than individual with constraints (0.098).

Trip chain types	Average number of other activities	Distribution among purposes			
		Education	Escort	Errand	Leisure
BW (Ho → Ho, <i>before work</i>)	1.13	0%	67%	0%	33%
HW (Ho → WB)	1.15	0%	96%	2%	2%
WW (WB → WB)	2.00	0%	100%	0%	0%
WH (WB → Ho)	1.29	2%	39%	40%	20%
AW (Ho → Ho, <i>after work</i>)	1.08	2%	11%	24%	64%

Table 5: Average numbers of activities/trips and distribution by purposes.

	Escort		Errands		Leisure	
	Home-Work (HW)	Work-Home (WH)	Work-Home (WH)	Work-Home (WH)	After Work (AW)	
Start working hours	Fixed	Flexible	Fixed	Flexible	Fixed	Flexible
Temporal Constraints						
Arrive later	80%	68%	91%	72%	31%	18%
Departure earlier	60%	35%	91%	58%	77%	35%
Other day	90%	94%	91%	86%	23%	44%
Other time	100%	91%	82%	72%	46%	32%
Spatial Constraints						
Other place	100%	100%	100%	97%	46%	21%
Social Constraints						
Other person	50%	47%	73%	39%	31%	53%
Decide yourself	70%	53%	73%	58%	77%	35%
Exclude activity	90%	94%	91%	97%	31%	68%
Constraints on arriving late at work	Yes	No	Yes	No	Yes	No
Temporal Constraints						
Arrive later	72%	69%	89%	68%	39%	4%
Departure earlier	56%	31%	74%	61%	78%	17%
Other day	89%	96%	89%	86%	35%	42%
Other time	89%	96%	84%	68%	39%	33%
Spatial Constraints						
Other place	100%	100%	100%	96%	43%	13%
Social Constraints						
Other person	50%	46%	47%	46%	43%	50%
Decide yourself	61%	54%	58%	64%	52%	63%
Exclude activity	94%	92%	95%	96%	52%	63%

Table 6: Comparison between flexibility in start working hours and restrictions in the departure time

Table 6 reports the analysis of the temporal, spatial and social constraints for the most relevant activities and trip chains (the ones with the highest frequency). Separate analyses are reported for fixed/flexible working hours and for individuals with full/no constraints on how late they can arrive at work. As expected, escorting trips are mostly constrained in almost all the dimensions (temporal, spatial and social), while errands and leisure activities are the most flexible. Interestingly leisure activities are less constrained when realised

within the main tour around work than when they are realised in the second tour. Individuals with fixed working hours are more constrained than individuals with flexible working hours, especially in the escorting and errands activities, while they have less constraints in the leisure activities. The analyses for the individuals who have or do not have constraints on how late they can arrive at work follows a similar pattern. As mentioned in Section 3 we performed a principal component analysis based on the type of activity, trip chain and the type of constraint. We found that each type of activity in a trip chain groups separately. This was expected because in our sample individuals perform simple tours with fewer activities concentrated in only one trip chain. Hence, with our sample the analysis by trip chain or tours is more suitable. Regarding constraints, the pattern is that activities with temporal constraints (i.e. that cannot be realised another time or another day) tend to be also spatially constrained. It is also more likely that these activities cannot be excluded. This effect is more marked for escorting activities carried out in each trip chain that tend to be either constrained or flexible in all the dimensions.

4 Model specification

Following the common formulation of the scheduling model (SM) and the typical mixed logit specification for panel effects, we assume that travellers face a discrete number of alternative departure times and they choose according to the following utility specification:

$$U_{jnt} = ASC_j + \beta_n^{TT} E(TT_{jnt}) + \beta_n^{TC} TC_{jnt} + \beta_n^{SDE} E(SDE_{jnt}) + \beta_n^{SDL} E(SDL_{jnt}) + \beta_n^{LP} LP + \beta^{SE} SE_n + \beta^{FC} FC_n + \mu_{jn} + \varepsilon_{jnt} \quad (1)$$

Where U_{jnt} is the utility for individual n associated to alternative j , in choice task t . $E(TT)$ is the expected travel time that accounts for the travel time variability. $E(SDE)$ and $E(SDL)$ are the expected scheduling delay for early and late arrival respectively. TC is the travel cost and LP is the late penalty dummy variable. SE is a vector of individual socio-economic characteristics, while FC is a vector of dummy variables to account for the effect of daily activities and flexibility constraints as defined in Section 2.2. Finally ε_{jnt} is a typical extreme value type 1 random terms that generates the multinomial logit probability, while μ_{jn} is a random term distributed normal that accounts for panel correlation among repeated observations from the same individual. Following Walker et al. (2007) we account for panel effect estimating two variances in the alternatives departure earlier and later and one correlation term between these two alternative. This reduces estimation time and makes the interpretation of the random effects easier, as the variance can be interpreted as the variation in the utility relative to the current departure time.

Following Noland et al. (1998), Small et al. (2000), and Börjesson (2007) we define $E(TT)$ as the sum of the travel weighted by the probability (p_i) that each travel time occurs:

$$E(TT_{jnt}) = \sum_{i=1}^I p_i \cdot TT_{jnti} \quad (2)$$

Analogously $E(SDE)$ and $E(SDL)$ are the expected scheduling delay for early and late arrival respectively, and are defined as:

$$E(SDE_{jnt}) = \sum_{i=1}^I p_i \cdot SDE_{jnti} = \max(-DT_{jnt} + E(TT_{jnt}) - PAT; 0) \quad (3)$$

$$E(SDL_{jnt}) = \sum_{i=1}^I p_i \cdot SDL_{jnti} = \max(0; DT_{jnt} + E(TT_{jnt}) - PAT) \quad (4)$$

If a traveller arrives at his/her preferred arrival time (PAT) then SDE and SDL will equal zero. This yields that the individual will not experience disutility from rescheduling. Note that TT is the total travel time from origin to destination, which in principle is a function of the departure time (DT). Similar TC is the travel cost with respect to DT . Note also that $\sum_{i=1}^I p_i = 1$.

We allowed the marginal utility of all the LOS attributes to depend on the individual socio-economic characteristics, the activities performed during the day and the flexibility constraints. The coefficients of the LOS attributes (X) then take the following general form:

$$\beta_n^X = \beta^X + \beta^{X,SE} SE_n + \beta^{X,FC} FC_n \quad (5)$$

Our model is then a Mixed Logit (ML) model where the unconditional probability is the integral over the random terms μ of the multinomial logit conditional probability that individual n chooses the sequence \mathbf{j} of alternatives $\mathbf{j} = \{j_1, \dots, j_t, \dots, j_T\}$ across the T choice tasks:

$$P_{n\mathbf{j}} = \int_{\mu} \prod_t P_{n j_t}^{MNL}(\mu) d\mu \quad (6)$$

5 Results

In this section we discuss the results from the model specification described in Section 4. All models were estimated using PythonBiogeme (Bierlaire, 2003; Bierlaire and Fretschler, 2009). We first estimated simple ML models with only the Level-of-Service (LoS) attributes that were included in the SP experiment, with the objective to compare and discuss the effect of measuring flexibility at work. Then we analysed the effect that the “activities other than work”, and their constraints, have on preferences for departure time to work. We discussed first the estimation results and then some policy implication in terms of their impact in the shift of the demand predicted.

5.1 Flexibility at work

Following all the relevant literature on departure time choice we began by estimating two models one that accounts for the effect of fixed and flexible start working hours (M1) and another model that accounts for the effect of having or not having constraints at work (M2). Table 6 reports the models estimated and the trade-offs (point values and intervals confidence).

Firstly we note that all coefficients in all models have the right sign, according to the microeconomic theory, and are highly statistically significant (p-values < 0.01), the only exception being the extra penalty for lateness (DL), which is not statistically significant for those with flexible work times (M1), and those with no restrictions on how late they can arrive at work (M2). This result is correct because flexible workers do not care (or at least care less) about being late. We also note that the scheduling delay for late arrival has a lower marginal utility than the scheduling delay for early arrival ($\beta_{E(SDL)} < \beta_{E(SDE)} < 0$) in all the models. This is expected as people care more about being late and similar findings can be found in numerous studies (Hendrickson and Planke, 1984; de Jong et al., 2003; Hess et al., 2007a; 2007b; Börjesson, 2007; 2008; Asensio and Matas, 2008; Koster et al., 2011; Arellana et al., 2012; Koster and Verhoef, 2012). Only very few studies (Börjesson, 2009; Arellana et al., 2012) does not support this trend. In our sample the marginal utility of $E(TT)$ is higher than both $E(SDE)$ and $E(SDL)$, hence the main priority for the respondents is travel time, and less importantly, the scheduling delays. This result is more marked for people with flexible working hours (or no constraints) than for those with fixed working hours (or constraints), which reflect the fact that flexibility is associated with less sensitivity to rescheduling. The ratios between $E(SDE)/E(TT)$ and $E(SDL)/E(TT)$ in our sample is lower than what found in the international literature. We compared our

results with the meta-analysis performed by Börjesson (2009). The WTPs for travel time are in line with the Danish official values. In our sample flexible (no restriction) individuals are willing to pay approximately 10€/hr on average for saving one minute of travel time, while fixed individuals are willing to pay approximately 12€/hr on average. The official Danish values, however, do not distinguish between flexible and fixed individuals, so in order to perform a direct comparison we compared the official Danish values with the weighted WTP in our sample, and found that they are very similar, i.e. approximately 11€/hr.

Estimates	M1				M2			
	Value	Robust t-test	Value	Robust t-test	Value	Robust t-test	Value	Robust t-test
	Fixed Hours		Flexible Hours		Constraints		No Constraints	
ASC (Early Departure)	-1.150	-1.80	-1.570	-3.16	-1.080	-1.90	-1.540	-2.84
ASC (Late Departure)	-0.948	-1.64	-0.875	-1.89	-0.620	-1.18	-1.020	-2.11
E(TT)	-0.137	-3.63	-0.238	-8.13	-0.159	-4.67	-0.246	-7.89
TC	-0.090	-3.93	-0.184	-8.65	-0.104	-4.86	-0.194	-8.28
E(SDE)	-0.052	-4.12	-0.041	-4.18	-0.058	-5.00	-0.035	-3.36
E(SDL)	-0.115	-5.46	-0.085	-8.44	-0.129	-8.30	-0.073	-6.40
DL	-0.632	-2.54	-0.076	-0.42	-0.654	-3.21	0.250	1.17
Generic for all sample				Generic for all sample				
St.dev (Early Dep)	-2.380	-10.16			-1.200	-3.46		
St.dev (Late Dep)	2.380	12.71			2.470	12.72		
Corr (Early-Late)	0.309	0.26			2.100	9.99		
Number of draws		1000				1000		
Number of observations		2515				2515		
LL(max)		-1790.37				-1779.61		
Rho2 (C)		0.330				0.340		

WTP [DKK/min]- Trade-offs

	Fixed hours	Flexible Hours	Constraints	No Constraints
E(SDE)/TC	0.577	0.224	0.562	0.179
95% Interval confidence	(0.237 - 1.448)	(0.108 - 0.382)	(0.278 - 1.146)	(0.068 - 0.33)
E(SDL)/TC	1.283	0.463	1.240	0.374
95% Interval confidence	(0.667 - 2.864)	(0.323 - 0.661)	(0.779 - 2.227)	(0.237 - 0.567)
E(TT)/TC	1.529	1.293	1.529	1.268
95% Interval confidence	(0.859 - 2.567)	(1.062 - 1.564)	(1.018 - 2.259)	(1.034 - 1.545)
E(SDE)/ E(TT)	0.377	0.174	0.367	0.141
95% Interval confidence	(0.175 - 0.889)	(0.09 - 0.277)	(0.202 - 0.687)	(0.058 - 0.243)
E(SDL)/ E(TT)	0.839	0.358	0.811	0.295
95% Interval confidence	(0.423 - 2.05)	(0.247 - 0.521)	(0.502 - 1.503)	(0.185 - 0.455)

Table 7: Basic scheduling models: comparing two ways of measuring flexibility at work

Following on from Hendrickson and Planke (1984) and Polak and Jones (1994) we also tested a specification with the squared E(SDL) and E(SDE). In line with their results, we found that individuals with fixed working hours have a decreasing marginal disutility as the scheduling delay increases. However, this effect became not significant when random heterogeneity was added. We found significant random heterogeneity around the mean value for both the scheduling delay for early and late arrival. However, around 50% of our sample did not fulfil the microeconomic conditions, especially for the scheduling delay for early arrival. We then decided not to use this specification further. Finally, it is worth mentioning that all models were also estimated accounting for systematic heterogeneity due to differences in SE characteristics (in particular, age, presence of children, marital status and so on), but none of the effects were very statistically significant (p-value < 0.05).

Looking at the comparison between fixed and restriction (or flexible and no restriction), results in Table 7 suggest that the way information on flexibility is requested does not seem to affect modelling results and can be used interchangeably as done in the current literature: the H0 hypothesis that the coefficients estimated in model M1 are the same as those estimated in model M2 was rejected at 0.10 level of significance. Moreover, the point estimates of the trade-offs computed in M1 are always within the 95% interval confidence of the

trade-offs computed with M2, and vice versa. However, results also clearly show that, in our dataset, the information on fixed/flexible working hours does not allow us to reveal differences in preferences for scheduling delay later (the H0 hypothesis that the coefficients for ESDL are the same between fixed and flexible people cannot be rejected at 0.10 level of significance). At the same time results suggest also that information on fixed/flexible working hours better allows us to capture the differences in travel time and cost preferences. It is reasonable that the preference for travel time and cost are more closely related to general working conditions, such as fixed/flexible working hours, while preferences for rescheduling late to conditions related to the specific trip. These specific results can depend on the context of application and the data collected, but they confirm that the way we ask information about flexibility at work might allow revealing different types of effects. In our case, depending on how the flexibility information is asked leads us to different conclusion in terms of demand sensitivity to scheduling delay late. In particular Model M1 would wrongly estimate the WTP for reducing *SDL* in 46% of our sample. Model M1 estimates that individuals with flexible working hours are willing to pay 10 euros per hour, but 30% of these individuals have constraints on how late they can arrive at work, so their willingness to pay is indeed around 3 euros per hour (according to Model M2). Analogously Model M1 estimates that individuals with fixed working hours are willing to pay 3.70 euros per hour, but 16% of them do not have constraints on how late they can arrive at work, so their willingness to pay is indeed around 10 euros per hour.

The preference for scheduling delay early is never significantly different whatever flexibility at work is used. We note that most of the studies discussed in the literature reported differences in the $E(SDE)$ depending on the level of flexibility at work. However, based on the t-test for generic coefficients, in several of these studies (e.g. de Jong et al., 2003; Börjesson 2007; 2008; 2009 and Kristoffersen 2013) the $E(SDE)$ does not seem to be significantly different between fixed and flexible respondents, confirming our findings. Disregarding this effect leads to overestimate the WTP for reducing *SDE* for individual with unadjustable work time and underestimate the WTP for reducing *SDE* for individual with adjustable work time.

5.2 Flexibility on daily activities other than work

In this section, we discuss the effect of daily activities and constraints. Model M3 in Table 8 shows the best model that includes only the flexibility effects at work (it summarises models M1 and M2 in Table 7), model M4 shows the effect of the aggregate measures of flexibility discussed in Section 3 (*trip complexity and Shannon's entropy*) and the disaggregate effects of the most relevant activities performed in specific trip chains, and their constraints.

Results from model M4 clearly confirm our second hypothesis that realising other activities during the day affects the departure time choice for the trip to work. Model M4 is statistically superior to model M3 (the Likelihood Ratio test is rejected at 0.01 level of significance). Results show that for individuals with constraints at work, the more complex the main tour around work (i.e. the higher the number of *other* activities performed, no matter whether constrained or not) the higher the penalty for rescheduling. Both early and late penalties were affected, but only the penalty for rescheduling the departure time early was highly significant. Individuals without constraints at work are not affected by the number of other activities but by how they are scheduled within the main tour (i.e. *entropy*). They are more likely to reschedule, and if they have *other* activities in more than one trip chain in the main tour around work, they prefer to reschedule early probably to have the possibility to manage all activities. Note that the maximum *entropy* in our data is 0.69, the marginal utility of $E(SDE)$ is then always negative.

Results from model M4 also confirm our third hypothesis that individuals without constraints at work are more affected by the constraints on *other* activities. This effect is particularly relevant for the *other* activities realised in tours not around work (namely home-based tours realised after returning from work) where it is clear that the penalty to reschedule the departure time is due to leisure activities spatially or socially constrained realised in the tour after the return from work. An activity realised after returning home is usually less tightly linked to the work trips (there might be a buffer of time spent at home before the new activity starts) hence it is expected that simply having activities in a home-based tour after work (AW) does

not affect departure time. However, if the activity is constrained, then individuals' WTP to avoid delay (both late and early) at work increases. Indeed, individuals without constraints at work are willing to pay on average 3.80 euros per hour of *SDL* reduction. However, if they have social constraints in leisure activities carried out after returning home from work their WTP is around 11 euros per hour. Note that individuals with constraints on how late they can arrive at work are willing to pay 9.70 euros per hour of *SDL* reduction.

Estimates	M3				M4			
	Value	Robust t-test	Value	Robust t-test	Value	Robust t-test	Value	Robust t-test
	Fixed Hours		Flexible Hours		Fixed Hours		Flexible Hours	
E(TT)	-0.133	-4.65	-0.237	-8.93	-0.137	-4.59	-0.238	-9.01
TC	-0.086	-4.33	-0.178	-9.41	-0.084	-4.18	-0.180	-9.36
	Constraints		No Constraints		Constraints		No Constraints	
E(SDL)	-0.132	-9.44	-0.069	-6.57	-0.130	-8.98	-0.058	-5.38
DL	-0.398	-1.67	0.001	0.01	-0.484	-1.91	0.063	0.29
Activities in the main tour around work								
E(SDE) x Number of <i>Other</i> activities					-0.028	-2.98		
E(SDE) x Entropy of <i>Other</i> activities							0.065	2.42
Activities in trip chain HW								
E(SDL) x <i>Escort</i> activities with Temporal Constraints					-0.091	-1.65		
Activities in trip chain WH (dummy)								
E(SDL) x <i>Errands</i> activities							-0.055	-2.68
Activities in trip chain AW (dummy)								
E(SDL) x <i>Leisure</i> activities with Spatial Constraints							-0.149	-5.77
E(SDE) x <i>Leisure</i> activities with Social Constraints							-0.150	-7.82
	Generic for all sample				Generic for all sample			
ASC (Early Departure)	-1.130	-2.44			-1.120	-2.33		
ASC (Late Departure)	-0.833	-2.19			-0.698	-1.86		
E(SDE)	-0.048	-5.96			-0.045	-5.44		
St.dev (Early Dep)	1.980	4.72			1.730	2.28		
St.dev (Late Dep)	-2.400	-13.04			-2.450	-12.76		
Corr (Early-Late)	-1.440	-2.71			-1.790	-2.03		
Number of draws		1000				1000		
Number of observations		2515				2515		
LL(max)		-1779.20				-1756.57		
Rho2 (C)		0.351				0.356		
WTP [DKK/min]- Trade-offs								
	Fixed		Flexible		Fixed		Flexible	
E(SDE)/TC (<i>all sample</i>)	0.565		0.272		0.632		0.277	
E(SDL)/TC (<i>all sample</i>)	1.412		0.491		1.409		0.523	
	Constraints		No Constraints		Constraints		No Constraints	
E(SDE)/TC (<i>all sample</i>)	0.444		0.301		0.535		0.265	
No activities other than work					0.483		0.289	
<i>Leisure</i> activities with Social Constraints in trip chain AW							1.107	
E(SDL)/TC (<i>all sample</i>)	1.206		0.429		1.200		0.476	
No activities other than work					1.228		0.368	
<i>Escort</i> activities with Temporal Constraints in trip chain HW					1.095			
<i>Errands</i> activities in trip chain WH							0.637	
<i>Leisure</i> activities with Spatial Constraints in trip chain AW							1.332	

Table 8: Scheduling models: effect of flexibility on daily activities other than work

For individuals with constraints at work, the penalty for rescheduling late was affected by *escorting* trips with *temporal constraints* on the trip chain between home and work. Lizana et al. (2013) also found that escorting trips on the way to work increases the penalty for arriving late. However, we found that in our data the effect is due more to the temporal constraint than to the type of activity. This makes sense because it is the combination of the two temporal constraints at work *and* at the other activity on the same trip chain that causes the major penalty for rescheduling late. Typically escorting trips are constrained, but if they are not constrained it does not necessarily increase the penalty. At the same time any another activity that is constrained increases the penalty to late arrival.

5.3 Policy implication of a simple toll ring

In order to test how the estimated models perform, we applied our findings in a forecast scenario, more specifically, introducing a toll ring around Copenhagen. For the simulation, we used the current travel times reported by each individual and computed the level-of-service for non-chosen alternatives based on the Danish National Transport survey. Ten intervals of 15 minutes each were defined, except for the first and last intervals that were of 1 hour each. All models were recalibrated to adjust the alternative specific constants and the scale to the real departure times. To test the models in forecast, a simple policy was tested assuming a toll of 20 DKK (approximately 2.50€) to be paid in the peak period between 7:30-8:30; a toll of 10 DKK (approximately 1.25€) to be paid between 7:00-7:30 and 8:30-9:00; no toll before 7:00 and after 9:00. This case is a realistic one, as it reproduces the toll system discussed in Denmark. A price range of 10-20 DKK is also in line with the system implemented in Stockholm and Göteborg (Transportstyrelsen (SE), 2015a; 2015b).

Figure 1 shows the policy implication of the two different ways of measuring flexibility to work. Results clearly show that indeed the prediction is different depending on how the information at work is asked. In particular model M1 tends to overestimate the elasticity of individuals with flexible working hours, while model M2 tends to overestimate the elasticity of individuals with no constraints. This result is due to the fact that individuals with fixed/flexible working hours have different levels of constraints on how late they can arrive at work (1/3 of the workers with flexible working hours in our sample declared that they do have constraints), which affects the elasticity of the demand for departure time.

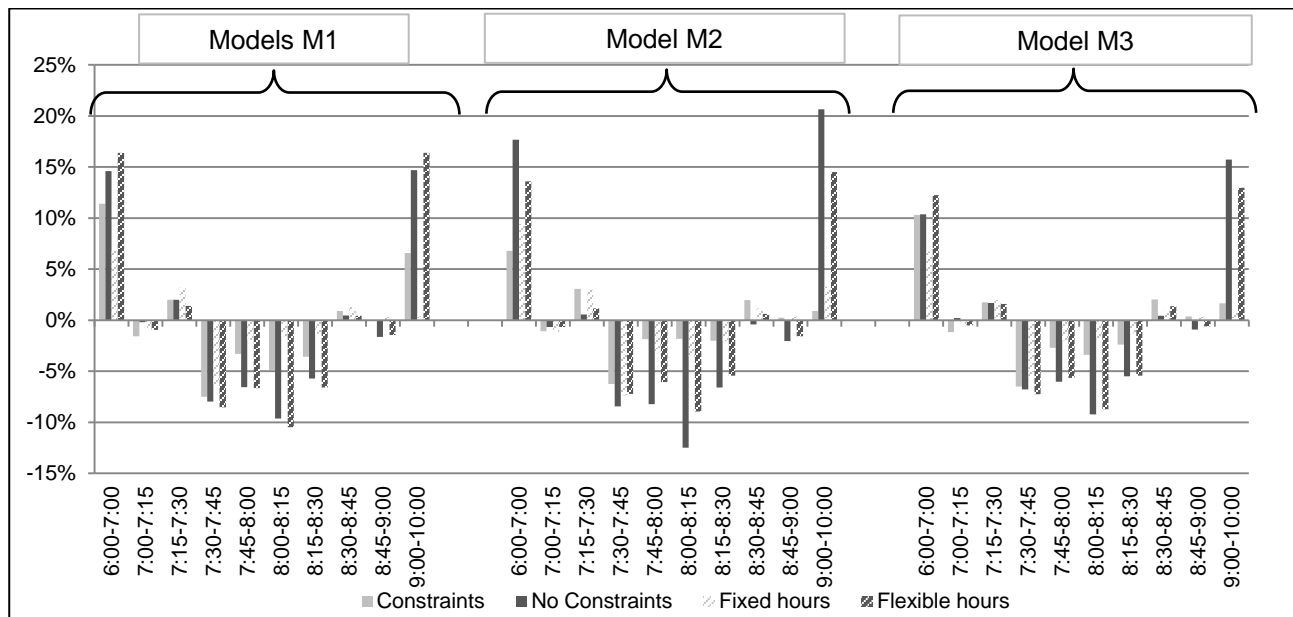


Figure 1: Shift in departure time predicted after the application of the policy: Effect of different ways of measuring flexibility at work

Figure 2 shows the effect on the shift in departure time predicted if we neglect the effect of other activities realised during the day and their constraints. Results clearly show that the shift in the departure time, especially toward a late departure time, is strongly overestimated when the effect of *other* activities and their constraints is not accounted for as in model M3. The segment that is predicted more wrongly is represented by individuals who have no constraints on how late they can arrive at work but have constraints on *other* daily activities. The reason is that constraints on activities other than work clearly impose constraints on the daily activity schedule and in particular on the departure time for work. Model M3 that neglects the effect of *other* activities and constraints strongly overestimate the willingness to shift, especially toward late departure times, predicting for example that almost 23% of the individuals with no constraints at work but with social constraints in leisure activities after returning home from work will shift departure time, while according to Model M4 only 8% will shift.

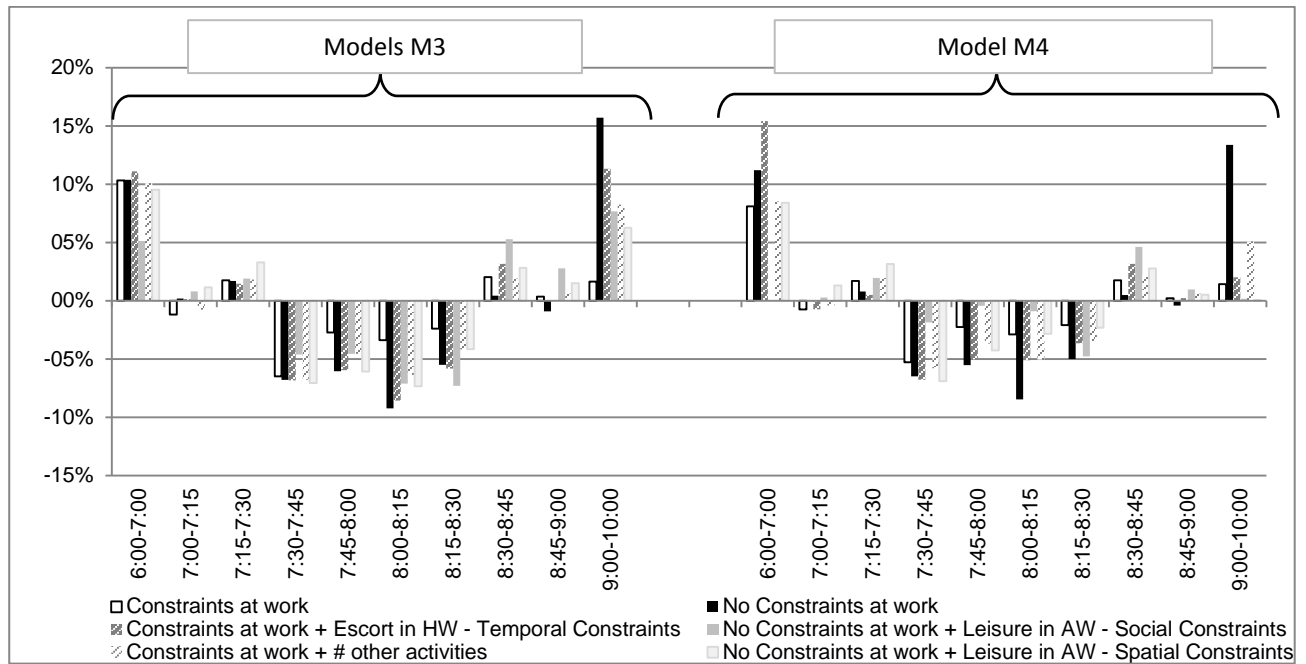


Figure 2: Shift in departure time predicted after the application of the policy: Effect of accounting for daily activity schedules and constraints.

6 Conclusion

In this paper we investigated the choice of departure time for car commuting trips in the morning. This analysis is carried out by creating an efficient design in which individuals are given three options where prices and time attributes are varied. The analysis, however, goes one step further and looks particularly at how flexibility or in-flexibility of the main activity (in this case work) as well as other activities during the day, influence the departure time choice. Accounting for these flexibility constraints is important because these will generally influence when individuals may decide to depart. In the paper, three hypotheses were put forward:

- The current ways of measuring flexibility might reveal different effects.
- Other activities carried out during the day may affect the willingness to switch (*WTS*), and willingness to pay (*WTP*) for avoiding rescheduling, departure time especially for individual with adjustable work times.
- Constraints on other activities would cause the *WTP* for rescheduling early or late to increase as it represent an extra cost.

We found that all three of our hypotheses were confirmed. If people are constrained in one way or the other, the cost of violating the preferred arrival time is considered more expensive than if people are flexible. However results clearly show that, in our dataset, the preferences for scheduling delay later is statistically different only between individuals with and without constraints at how late they can arrive at work, so the difference in the WTP for (avoiding) late arrival can be correctly estimated only if the information about flexibility is asked in terms of constraints at work. Since one third of the workers with flexible working hours declared in our survey to have restrictions in arriving late at work, their willingness to pay will be overestimated (almost doubled) if flexibility information is asked only in terms of fixed/flexible working hours. These specific results can depend on the context of the study, but they clearly prove that the specific way questions are asked affects the definition of flexibility at work and has an impact on the willingness to pay and willingness to shift estimated with the demand models. There is certainly not a single way for these surveys to ask about a person's activity flexibility, but this reinforces the renewed trend (Cherchi and Hensher, 2015) of complementing SP survey with in-depth interviews to explore better the nature and role of constraints at work.

Results also clearly show that activities other than work carried out during the day strongly affects the willingness to shift departure time. In particular both the number of activities other than work and how they are scheduled across trip chains is relevant in the distribution of departure time and has strong policy implication. Overall, neglecting the effect of daily activities other than work and their constraints strongly overestimate the willingness to shift toward early/late departure times. The type of activities and constraints is relevant but only if analysed at a trip chain level. This was especially the case for individuals without constraints on how late they can arrive at work, because the restriction in daily activities other than work imposes a restriction on the work activity itself. For example, we see that individuals without constraints at work but with social constraints in leisure activities carried out after returning home from work are willing to pay on average 11 euros per hour of *SDL* reduction, which is more than twice the WTP of individuals without constraints at work *and* without other activities (3.80 euros) and almost approximately the same WTP of individuals with constraints at work (9.70 euros). This of course has relevant policy implications. In a simple scenario that assumes a toll ring of 20 DKK in the morning peak, we found that a shift in departure time predicted if the effect of daily activities other than work and their constraints is not accounted for is almost 3 times bigger than if these effects are correctly taken into account.

In our data we were not able to identify clear patterns that allowed us to group type of activities, constraints and trip chain in categories. A larger sample is probably needed for that. However, our finding clearly suggest that studies on departure time should account for the daily activity schedule and possibly also the weekly activities, because flexibility can vary across days, as the activity schedule varies over the week. Finally, in this study we focused on work trips because the objective was to explore the effect of activities other than work and their constraints on the departure time to work. A more comprehensive investigations should include all travellers who can decide to shift their travel times or activity schedules and durations.

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Psychology meets microeconomics:

Accounting for the Theory of Planned Behaviour in departure time choice

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Abstract

Motivating people to change their departure time could play a key role in reducing peak-hour congestion, which remains one of the most prevalent transport problems in large urban areas. To achieve this behavioural change, it is necessary to better understand the factors that influence departure time choice. So far departure time choice modelling focussed mainly on objective factors, such as time and costs as main behavioural determinants. In this study, we derived psychological factors based on the Theory of Planned Behaviour, estimated them based on structural equation modelling, and included them into a discrete choice model. The psychological factors were measured based on an online questionnaire addressed to car commuters to the city centre of Copenhagen ($N=286$). The questionnaire additionally included a travel diary and a stated preference experiment with nine departure time choice scenarios. All psychological factors had a significant effect on departure time choice and could improve the model as compared to a basic discrete choice model without latent constructs. As expected, the effects of the psychological factors were different depending on framework conditions: for people with fixed starting times at work, the intention to arrive at work on time (as estimated by subjective norm, attitude, perceived behavioural control) had the strongest effect; for people with flexible working hours, the attitude towards short travel time was most relevant. Limitations, the inclusion of additional psychological factors and their possible interactions are discussed.

Highlights

- Psychological factors for departure time choice were derived from the Theory of Planned Behaviour
- Accounting for the Theory of Planned Behaviour in a discrete choice model improved the estimation
- All included psychological factors had a significant effect on departure time choice
- Intention to arrive on time was more relevant for people with fixed starting times
- Attitude towards short travel time was more relevant for people with flexible starting times

Keywords:

Departure time
Theory of Planned Behaviour
Hybrid choice model
Attitude
Intention

1 Introduction

Road traffic congestion remains one of the most prevalent transport problems in large urban areas as it decreases the attractiveness and liveability of cities. In addition, the fuel and time wasted in traffic have huge financial consequences as well as negative impacts on public health (e.g. Levy et al., 2010).

Congestion is related to commuting to work and a change of departure time could play a key role in reducing peak-hour congestion. A number of studies have shown that people are more likely to change their departure time to avoid congestion than to change their transport mode (Hendrickson & Planke, 1984; Hess et al., 2007; Kroes et al., 1996; SACTRA, 1994). The question is, however, how people can be motivated for this behavioural change. To answer this question it is necessary to better understand the psychological factors that influence departure time choice. While this question is of particular importance for both commuting by car and by public transport, the focus of this paper is on car commuting.

So far, departure time choice has mainly been investigated from a microeconomic perspective, considering objective factors, such as travel time, arrival time and travel costs as main behavioural determinants. The basic assumption of this rational choice approach is that individuals make a trade-off between costs, travel time and deviations from their preferred arrival time in such a way that their personal benefit is maximized. Later works also included travel time (un)reliability) accounting for uncertainty about the actual travel time during a journey, i.e. the unexpected delay (Arellana et al., 2012; Börjesson, 2007; 2008; 2009; Ettema et al., 2004; Koster & Verhoef, 2012; Lam & Small, 2001; Lizana et al., 2013; Noland & Small, 1995; 2000; Tseng et al., 2011). This concept, often referred to as travel time variability (TTV), is important because people might re-think their departure time choice under the condition of high travel time variability. The subjective importance of time reliability for transport choices was confirmed in a study based on Q-methodology (Cools et al., 2009).

A few studies approached departure time choice taking into account assumptions of prospect theory that goes beyond microeconomic theory into psychological theory (Fujii & Kitamura, 2004; Senbil & Kitamura, 2004). These studies point to the importance of the decision frame: Fujii and Kitamura (2004) in particular demonstrated that the choice of more or less risky departure times depends on commuters' working conditions and position. Thereby they indirectly proved the relevance of attitudes, namely the subjective importance of arriving at the preferred arrival time for departure time choice.

An alternative research strategy to the indirect measurement of people's preferences through their choices is the direct measurement of psychological factors that are assumed to influence behaviour by standardised items. The selection of these factors should preferably be based on a theoretical model. This strategy allows for the consideration of factors that go beyond specific preferences.

To our knowledge the only study that explicitly measured psychological factors in econometric models to explain departure time choice is Arellana (2012). He measured attitude towards being on time and towards changes in trip conditions, but finally did not include them into the departure time choice model. He included another latent factor, namely attitude towards flexibility, which was, however, not measured based on psychological items but through travel time information. He found that individuals with a strong attitude towards flexibility are more sensitive to travel time, and more likely to reschedule their departure time.

We expect that the understanding and prediction of departure time choice benefits from a combination of the psychological and the microeconomic perspective. In the present paper we approach this by investigating potentially relevant psychological factors of departure time choice and including them into a discrete choice model based on stated preference experiments. The selection of the psychological variables is based on the assumptions of the Theory of Planned Behaviour (Ajzen, 1991) as described in the following section. In Section 3, we present our specific hypotheses.

2 Accounting for the Theory of Planned Behaviour in departure time choice

The Theory of Planned Behaviour (TPB, Ajzen, 1991) can be regarded “as a social psychological variant of the general rational choice approach” (Bamberg, 2012, p. 222). Thus, one can regard it as a good starting point for the combination of microeconomic and psychological research. It is one of the most well-established psychological models of individual decision making. According to a meta-analysis of 185 studies it accounts for 27% and 39% of the variance in behaviour and intention, respectively (Armitage & Conner, 2001). In transportation research it has in particular been applied to explain and influence travel mode choice (e.g., Bamberg & Schmidt, 1998; 2001; 2003; Haustein & Hunecke, 2007; Heath & Gifford, 2002) and driving violations (e.g., Cestac et al., 2011; Forward, 2009; Møller & Haustein, 2014). According to the TPB, the intention to perform a given behaviour indicates people’s readiness to perform the behaviour, and it is a direct predictor of behaviour. Intention is influenced by attitude, subjective norm, and perceived behavioural control (PBC). Attitude is the degree to which the performance of the behaviour is positively or negatively valued. Subjective norm is defined as the perceived social pressure to engage or not to engage in the behaviour, while PBC refers to people’s perceptions of their ability to perform the behaviour. The latter is assumed to be a direct predictor of both intention and behaviour. The lower the actual control over a given behaviour, the more the influence of intention decreases in favour of PBC. In the context of travel mode choice, research on PBC mainly focused on beliefs related to the built environment (accessibility/transport infrastructure; cf. Bamberg, 2012). Haustein & Hunecke (2007) introduced the concept of perceived mobility necessities (PMN) to more directly address how the actual living situation (e.g. complex household routines due to children and employment) and resulting perceived travel demands influence car use. While PBC and PMN are correlated, merging them to one latent variable resulted in an unacceptable model fit, which indicates that they should be modelled as separate latent variables. The differentiation between PBC and PMN is expected to be also relevant for departure time choice: beliefs about the transport infrastructure are supposed to make it more or less difficult to arrive at the preferred arrival time, while the personal living situation and related perceptions of flexibility and time pressure are supposed to make people less willing to reschedule their departure time.

Departure time choice is a complex task, which to our knowledge has not yet been explicitly studied in the psychological literature. We suggest departure time choice to be determined by three behavioural intentions that may be in conflict with each other, namely (1) the intention to arrive at the preferred arrival time – or more specifically “on time”; (2) the intention to have short travel times; and (3) the intention to have low travel costs. In line with TPB, we expected all three intentions to be determined by attitude, social norm and perceived behaviour control as shown in Figure 1. In addition, we expect PMN to have a direct impact on departure time choice. Including indicators for all these psychological variables was not possible in the design of the present study,

so we had to choose those variables that we expected to have the highest added value when included into a discrete choice model.

The relevance of the attitude towards arriving on time for departure time choice was indirectly confirmed by Fujii and Kitamura (2004). They showed that people in a higher work-place hierarchy (as approximated by age) chose riskier departure time alternatives than people lower in hierarchy. This was assumed because of the different consequences of being late and thus the importance of being on time for both commuter groups, which refers to attitude. Similarly, we assume that the riskier choices are related to less perceived social pressure to arrive on time (subjective norm (SN)) and expect both factors, attitude and SN, to be highly related. We further assume that the intention to arrive at work on time is more relevant for people with fixed working hours than for people under flextime conditions, which is also in line with the finding of Fujii and Kitamura (2004) who showed that people under flextime conditions choose riskier departure time alternatives.

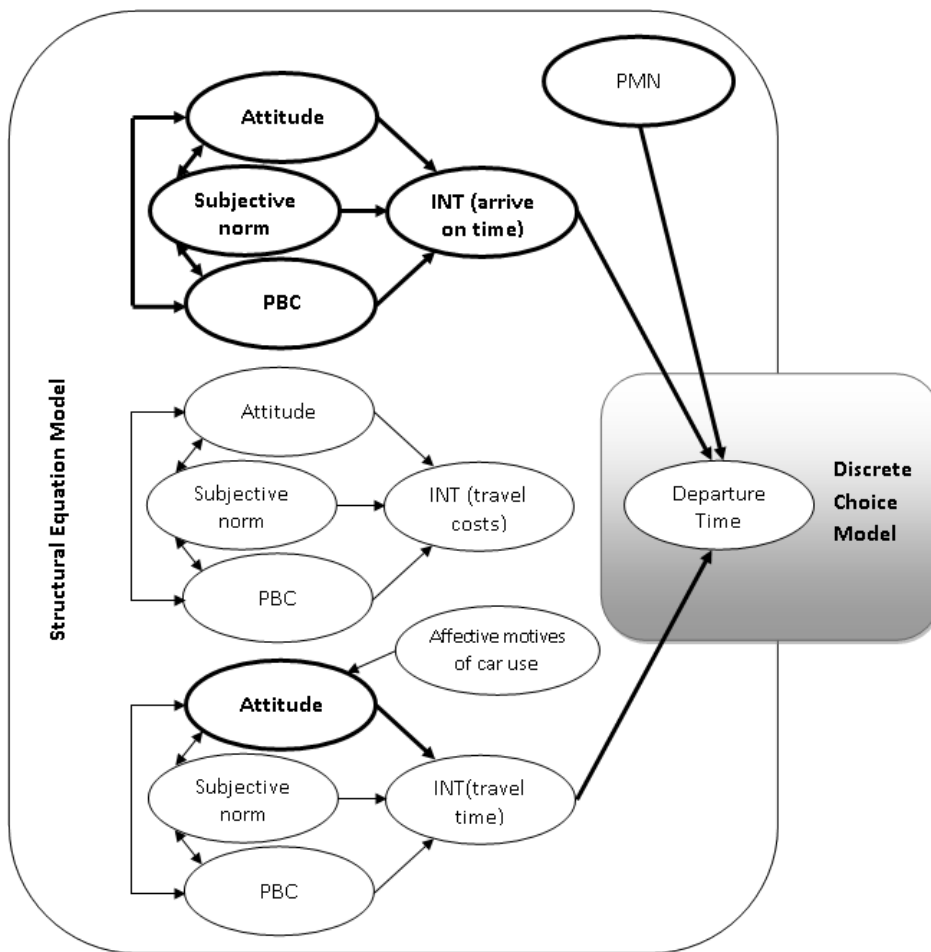


Figure 1: Selection of psychological constructs to be included in the discrete choice model (selected constructs and effects in bold)

With regard to minimizing travel time, we only included the attitude towards short travel time. It has been shown that travelling does not only serve the utility of arriving at the desired destination but also the utility of doing other activities while travelling (e.g. relaxing, thinking, transition between home and work) and also has an intrinsic utility (Mokhtarian & Salomon, 2001). Thus, people most probably differ with respect to the importance they allocate to short travel times,

depending, for example, on how much they like or dislike car driving or queuing. People who associate driving with symbolic and affective motives such as freedom, autonomy and passion might be more willing to accept longer travel times by car – and probably rather change their route than their departure time, while people who perceive driving as boring or stressful might find it more important to reduce travel time. These assumptions are supported by empirical results from Beirao and Cabral (2007) who on the one hand identified car users who appreciate the autonomy and flexibility of the car and “feel that they can change route and avoid traffic” (p. 484) and on the other hand captive car users who are nervous or worried about traffic jams and would prefer to use public transport, which would allow them to relax or make use of their time in a different way (p. 482). Subjective norm appears less relevant for minimizing travel time than for arriving on time, also because travel time is not directly observable by others. An exception might be the perceived social pressure of the partner in case of high family demands. Perceived control and intention are probably important, but may be partly captured by Perceived Mobility Necessities (PMN): People who perceive a high pressure to be mobile all the time, most probably intend to have short travel times but are at the same time more likely to be restricted in their possibilities of rescheduling their departure time.

Psychological factors related to minimizing travel costs were not considered. While instrumental motives (Jakobsson, 2007), in particular convenience and costs, are evaluated as important attributes of commuting trips (Anable & Gatersleben, 2005) they are found to be less useful to explain differences in car use as compared to affective and symbolic motives (e.g., Lois & Lopez-Saez, 2009; Steg, 2005). Similarly, we expect that the great majority of commuters would agree that it is important to have low travel costs, which would, however, not contribute much to the explanation of individual differences in departure time choice. To capture the effect of travel costs we think that the indirect measure through the choice in the experimental setting is the preferable method.

3 Hypotheses

Several studies, mainly in the transport field, have incorporated latent variables to better explain the discrete choice by capturing psychological constructs. However, none of them explored the effect of the full TPB and none of them studied the effect on departure time choice. To our knowledge, this paper is the first to integrate psychological and microeconomic theory to explain departure time choice.

Our main goal was to examine if the TPB is a useful model in the context of departure time choice and to which extent departure time is affected by psychological factors versus microeconomic evaluation of the characteristics of the alternatives. More specifically, we expected the intention to arrive at work on time, as predicted by subjective norm (SN), attitude, and perceived behavioural control (PBC), to have a significant impact on departure time choice as measured in the setting of a stated preference experiment. In addition, we expected perceived mobility necessities (PMN) as well as the attitude towards short travel time to have a significant direct effect on departure time choice.

Based on structural equation modelling (SEM) we first estimated the value of each psychological construct based on its indicators, as well as the intention to arrive at work on time by its predictors: attitude, SN, and PBC.

In a second step, intention and the other psychological variables were included in a discrete choice model (DCM) to test the following specific hypotheses:

- (1) Accounting for the TPB in a sequential approach significantly improves the model estimation as compared to a basic DCM without latent variables.
- (2) Accounting for the TPB significantly improves the model estimation as compared to a DCM including intention estimated solely by its own indicator variables.
- (3) The inclusion of attitudes regarding travel time and PMN further improves DCM.
- (4) Intention to arrive at work on time is more relevant for people with fixed working hours than for people benefitting from flexible time conditions.

4 Material and method

4.1 Questionnaire

A web-based questionnaire targeted at car commuters was constructed to collect the following information: (1) *travel behaviour*, including detailed information about the trips and activities performed by each respondent during his/her latest working day, (2) *stated preference data*, which allowed us to estimate respondents' preferences for departure time and for travel time, cost, and delay (i.e. level of service characteristics), (3) a set of *psychological variables* to estimate the constructs in relation to the TPB and (4) a set of *background variables* such as age, sex, income, location, household position and more importantly flexibility about the start/end of the working hours.

In the Stated Preference (SP) experiment different hypothetical but realistic scenarios were presented and respondents were asked to choose their preferred option in each scenario. Each scenario consisted of three possible departure times: the current departure time (i.e. the same as described in the *daily trip* part of the questionnaire), an earlier and a later departure time. Each scenario was described by four characteristics: departure time (DT), travel cost (TC), travel time (TT), and travel time variability (TTV). A total of 9 scenarios were presented to each respondent, where the values of the characteristics were varied according to specific rules that allow maximising the information about individual preferences that we can infer from the individuals' choices. Figure 2 shows an example of one scenario presented to respondents. More details on how the SP experiment was built can be found in Thorhauge et al. (2014).

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Transport survey 2013

Choice task 1 of 9 (Step 3 of 7)

What departure time do you prefer?

	Journey A	Journey B	Journey C
Departure time	08:00	07:30	07:00
Travel time	4 out of 5 times the travel time will be 24 minutes (arrival time 08:24) 1 out of 5 times the travel time will be 39 minutes (arrival time 08:39)	4 out of 5 times the travel time will be 30 minutes (arrival time 08:00) 1 out of 5 times the travel time will be 45 minutes (arrival time 08:15)	4 out of 5 times the travel time will be 21 minutes (arrival time 07:21) 1 out of 5 times the travel time will be 31 minutes (arrival time 07:31)
Cost	10 DKK	16 DKK	16 DKK
Your choice?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

<- Tilbage / vis forrige
Godkend / Videre ->

Figure 2: Example of a choice task for a respondent with preferred arrival time 8:00

Regarding the psychological variables, we included the constructs of the TPB (ATT_late, SN, PBC, INT), as well as perceived mobility necessities (PMN) and the attitude towards short travel time (ATT_time) as explained in Section 2. Each psychological construct was measured by three items on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Table 1 lists the items including their means and standard deviations as well as the internal consistencies of the psychological constructs. Most internal consistencies lie between .9 and .8 and can thus be described as good, whereas PBC and ATT_time with values between .7 and .6 are just acceptable. In both cases (PBC and ATT_time), deleting one item would further decrease the internal consistency. Thus, rather than replacing existing items, we recommend an extension of the number of items to measure these latent variables.

Table 1: Psychological constructs and their indicators

Latent variables			Indicators	<i>M</i>	<i>SD</i>	Cronbach's α
TPB						
Attitude towards being late	ATT_late_1	It is very important for me to be at work on time.	4.06	1.14	.85	
	ATT_late_2	Coming too late to work is very unpleasant for me.	3.73	1.29		
	ATT_late_3	It is problematic for me to be late for work.	3.63	1.35		
Subjective norm	SN_1	My colleagues think that I should be at work on time.	3.31	1.41	.86	
	SN_2	My boss thinks that I should be at work on time.	3.35	1.45		
	SN_3	People, who are important to me, think I should be at work on time.	3.27	1.35		
Perceived behavioural control	PBC_1	It is easy for me to be at work on time.	4.18	0.96	.65	
	PBC_2	It is difficult for me to be at work on time. ^a	4.57	0.75		
	PBC_3	It is possible for me to be at work on time if I want to.	4.22	1.08		
Intention	INT_1	I intend to be at work on time in the near future.	4.38	0.92	.81	
	INT_2	I intend to avoid delays in arrival time at work in the near future.	3.92	1.15		
	INT_3	I plan to be at work on time in the near future.	4.31	0.97		
Additional latent variables						
Attitude towards short travel time	ATT_time_1	It is very important for me to have short TT to/from work.	3.77	1.12	.67	
	ATT_time_2	Having a long TT to/from work is very stressful for me.	3.53	1.22		
	ATT_time_3	I don't care about long TT to my work. ¹	4.35	0.95		
Perceived mobility necessities	PMN_1	The organization of my everyday life requires a high level of mobility.	3.40	1.25	.83	
	PMN_2	I have to be mobile all the time to meet my obligations.	3.16	1.29		
	PMN_3	My work requires a high level of mobility.	2.94	1.28		

Notes: All indicator statements were measured based on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

^a Item has been re-coded.

4.2 Procedure and participants

The target population of this study were 18-65 years old car commuters who worked in the city of Copenhagen. An additional criterion was that individuals had travelled to work in the morning peak period and experienced congestion or queuing on the way to work, as this would prove a vital incentive to reschedule (or at least rethink) their departure time.

The data was collected contacting individuals directly at their work place. Two universities and three of the biggest companies and public organisations in Copenhagen were selected. For all individuals employed at universities, email addresses were publically available on the webpage of the universities, so that they could be contacted directly. For the individuals working in the companies we contacted a manager in each company and asked for permission to get access to email lists of the employees. All types of employees were included in the sample. More than 10,000 invitations were distributed via email resulting in 923 fully completed questionnaires. 286 of these fulfilled the criteria of the target population as specified above.

Table 2 summarises the main characteristics of our sample ($N=286$). Demographics and travel and workplace characteristics were compared with data from the Danish National Travel Survey (TU, Christiansen, 2012). For the comparison we only included people living in the Greater Copenhagen Area who commuted by car between 6-10 a.m. As can be seen, our sample differs significantly

from the TU sub-sample in many categories. This was to be expected because of the choice to recruit our sample specifically in the academia where people typically have flexible working hours, a higher education level and a higher amount of working hours.

Table 2 also compares the distance travelled and the travel time between our sample and the TU sub-sample. In our sample short trips (=less than 10 km) and long distance trips (=more than 50 km) are underrepresented. Finally, it is also interesting to note that 68% of the individuals in our sample commute by car to work on a daily basis, 26% several times a week, and only 6% on a weekly basis or less, which provides an indication of the extent to which the trip is habitualized. Unfortunately, this information is not available in TU data.

Table 2: Descriptive statistics of the sample and comparison with TU survey

		Sample (N=286)	Danish National Travel Survey (N=4410)	Difference between samples	
				χ^2	p
Gender	Male	50.3%	55.9%	3.34	.188
	Female	49.7%	44.1%		
Age	18-29	3.1%	6.7%	14.60	.067
	30-39	22.7%	22.7%		
	40-49	30.4%	34.0%		
	50-59	28.0%	26.4%		
	60+	15.7%	10.1%		
Household type	Single	11.5%	11.9%	1.27	.996
	Single with child/children	5.2%	4.1%		
	Couple	29.0%	30.8%		
	Couple with child/children	54.2%	53.1%		
Education	Elementary	0.3%	5.9%	137.11	< .001
	High school	1.0%	7.9%		
	University	93.4%	58.5%		
	Other/unknown	5.2%	27.8%		
Work flexibility	Fixed start/end work time,	33.6%	36.4%	301.11	< .001
	Flexible start/end work time	65.0%	22.6%		
	Unemployed/unknown	1.4%	40.9%		
Work hours per week ^a	Less than 37 hours	8.4%	16.6%	91.93	< .001
	37 hours	29.4%	49.1%		
	More than 37 hours	62.2%	34.2%		
Individual income [1000 DKK]	Low (<300)	4.5%	12.9%	62.10	< .001
	Medium (300-600)	49.7%	53.4%		
	High (>600)	36.4%	18.3%		
	Unknown	8.7%	6.9%		
Commuting distance [km]	1-10	25.2%	33.0%	29.05	< .01
	11-20	30.4%	27.6%		
	21-30	20.6%	17.3%		
	31-40	13.6%	10.9%		
	41-50	9.4%	5.5%		
	More than 50	0.7%	5.7%		
	<i>Mean (std. dev)</i>	<i>21.2 (12.9)</i>	<i>22.1 (24.4)</i>		

^a37 hours is the norm for a standard working week in Denmark. The number of working hours includes the total working hours per week regardless of whether the work is conducted from the work place or another location, e.g. home).

The sample consists of 286 individuals, each presented with 9 SP choice tasks. After a cleaning of the survey, 2515 observations were used for estimation.

5 Models and Results

In this section we first describe the results of the structural equation model (SEM), and then the integration of the TPB and additional psychological factors into the discrete choice models (DCM).

5.1 Intention to arrive at work on time

We estimated the latent variables for each of the latent construct, as well as the full Theory of Planned Behaviour (TPB) for the intention to arrive at work on time. Figure 3 shows the results of the SEM, in which intention is predicted by attitude, subjective norm, and perceived behavioural control in line with the assumptions of the TPB. The latent constructs were measured by the indicator items described in Table 1. The model was estimated using SPSS AMOS Version 22.

While all predictors of intention were statistically significant ($p < .001$), a positive attitude towards being at work on time had by far the strongest effect on intention ($\beta = .61$). The social pressure to arrive on time, as captured by subjective norm, and perceiving it easy to arrive on time, had similar but lower effects ($\beta = .23$; $\beta = .24$). As expected, attitude and subjective norm were strongly correlated ($r = .52$; $p < .001$), while the correlations with PBC were not significant ($p > .10$).

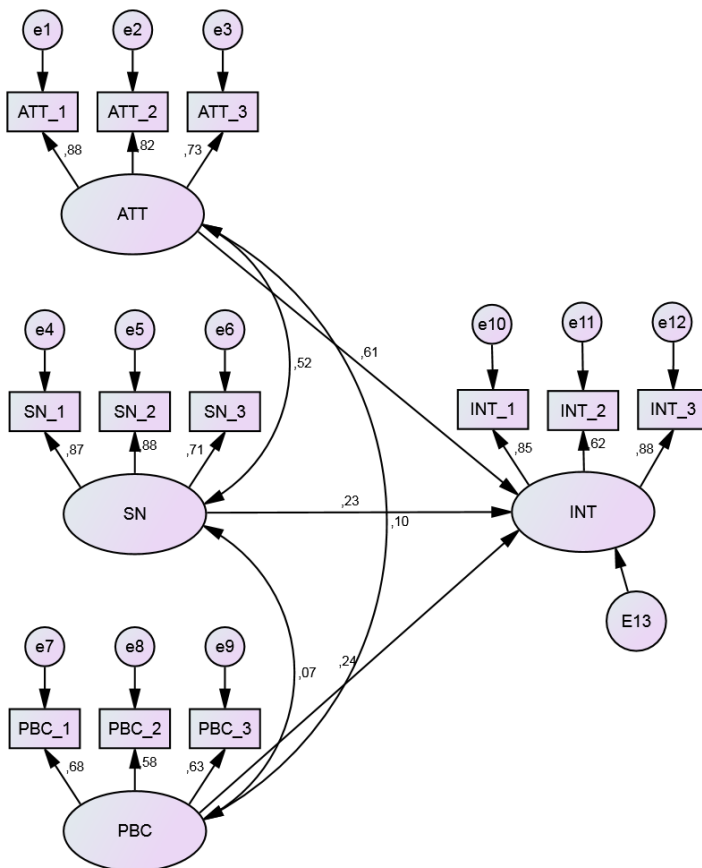


Figure 3: Intention to arrive at work on time

Notes: $N = 286$; Fit statistics: CFI = .952; RMSEA = .074; SRMR = .0523; Chi2 = 123.89, df=48

The model's fit statistics are provided in the legend of Figure 1. Hu and Bentler (1999) suggest a two-index presentation strategy to evaluate model fit. Among others, CFI $> .95$ in combination with SRMR $< .09$ are recommended, especially for small sample sizes ($N \leq 250$), to conclude that the

model fits the observed data well, which is the case in our example. Intention as estimated in the model was included in the DCM as described below.

5.2 Integrating TPB in the departure time choice

The microeconomic approach to departure time choice is based on the concept that individuals make a trade-off between travel time and penalties for rescheduling, i.e. being early or late. For that we rely on the scheduling model (Small, 1982) that assumes that travellers (n) choose the alternative (j) that gives them the highest utility (U), defined as a linear combination of attributes describing the alternatives. In the latest version of the scheduling model the discrete choice among departure time alternatives is expressed as a function of travel cost (TC); the expected travel time ($E(TT)$) from origin to destination weighted by the probability of experiencing additional (unforeseen) travel time; the weighted expected scheduled delay early ($E(SDE)$) and late ($E(SDL)$), i.e. the difference between the individual preferred arrival time and the actual arrival time, and an extra penalty for being late (DL).

The typical scheduling model (SM) assumes that individual preferences are affected only by attributes that measure the level-of-service (LOS). We extended the SM to account for the fact that individual preferences can be (and typically are) also affected by latent effects, such as attitudes and intentions. The extended SM takes the following form:

$$U_{jnt} = ASC_j + \beta_{TT}E(TT_{jnt}) + \beta_{TC}TC_{jnt} + \beta_{SDE}E(SDE_{jnt}) + \beta_{SDL}E(SDL_{jnt}) + \beta_{DL}DL_{jnt} + \beta_{LV}LV_n + \mu_{jn} + \varepsilon_{jnt} \quad (1)$$

Where LV_n is a vector of latent variables for individual n estimated in the structural equation model (SEM), ASC is a vector of constants specific for each alternative j , ε_{jnt} , is an error term distributed identically and independently extreme value type 1, while μ_{jn} is a normally distributed error component that captures the correlation among choice tasks (t) answered by the same individual. All the other attributes have the meaning explained above and the β_s are the parameters, associated to each attribute, to be estimated.

The model in the equation (1) is called a hybrid choice model (Ben-Akiva et al., 1999; Walker, 2001), because it integrates the typical discrete choice model (namely the SM) with the structural equation model (for the LV). In this paper, we used a sequential estimation, which is a two-step process. First the latent variables (i.e. intention with regard to being late, PMN, and attitude with regard to having short travel times) were estimated based on SEM and afterward included in the discrete choice model (DCM) as explanatory variables.

The sequential estimation is used when the hybrid choice models are particularly complex (as in our case) and hence difficult to converge and to be empirically identified. The sequential estimation however can result in potentially biased estimators, which are not guaranteed to be consistent, and can underestimate the standard deviation of the parameters. According to Yanez et al. (2010) the problem with biased estimates can be solved by adding a random term to the LVs. However, empirical tests conducted by Raveaux et al. (2010) using real and synthetic data showed that (albeit only for the MNL model) both sequential and simultaneous estimation methods are unbiased and that the difference does not affect the model estimates significantly. Due to the complex set of latent constructs used in this study, the straightforward approach of the sequential estimation was highly desirable.

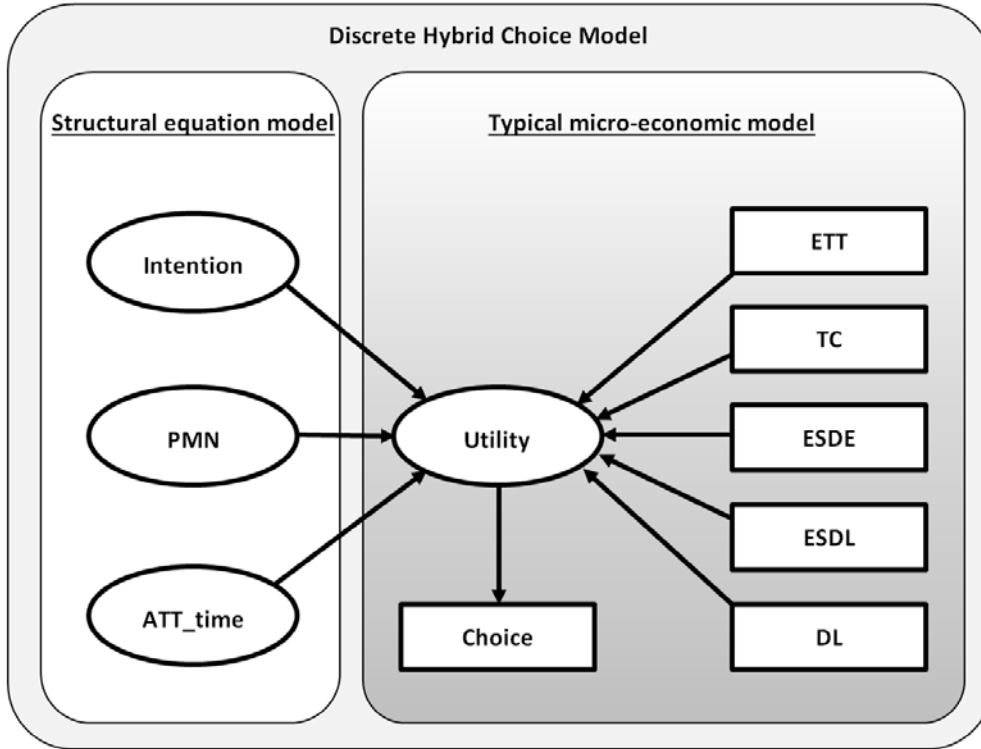


Figure 4: Incorporating latent variables into the micro-economic discrete choice framework

Table 3 shows the results of the model estimated. For purposes of comparison we first estimated the basic scheduling model alone, without any latent effects. The remaining models in Table 3 are hybrid choice models, accounting explicitly for latent effects as justified by the Theory of Planned Behaviour. All models account for panel correlation among the stated preference observations answered by the same individual n , following the specification in Walker et al. (2007). The models were estimated using PythonBiogeme (Bierlaire, 2003; Bierlaire & Fretschler, 2009).

As expected, all coefficients in the *scheduling model* part were negative and significant ($p < .001$). The negative sign was as expected, as it indicates that utility decreases if any one of the attributes increases. In other words, if an attribute increases (e.g. travel time or scheduling delay) the probability of selecting that departure time option decreases. Thus, (perfectly rational) individuals seek to balance the attributes by choosing the departure time that gives them the highest overall utility (i.e. lowest disutility). The most important attribute for the respondents in our sample was travel time, while the scheduling penalties was the least important as indicated by the marginal utility of $E(TT)$ being higher than both $E(SDE)$ and $E(SDL)$. This can be explained by the fact that 65% of the respondents had flexible working start times, so that their exact arrival time is probably less important. Respondents whose main priority is travel time are likely to select either the early or the late departure option to lower their travel time.

The latent variables part shows the direct influence of the psychological factors in the choice of departure time. HCM1 includes intention as a separate variable, explained solely by its three indicator items (see Table 1). By contrast, HCM2 includes intention as explained by a set of lower level latent variables, ATT_late, SN, and PBC. Both models only include the LV in the alternative of being late, as the parameter for early departure was not significant in the other alternatives, and

was thus removed. As expected the parameters were negative. This means that individuals who intend to be at work on time *gain* disutility of being late, but since the parameter was not significant for early departure, it means that they are indifferent if they arrive early or arrive on time. We estimated specific parameters for individuals with fixed working hours and flexible working hours, and as expected the penalty of late arrival is much more prevalent for individuals with fixed arrival. Comparing intention in HCM1 and HCM2 we found that the value of the LV is slightly higher and more significant when intention is explained by ATT_late, SN, and PBC (as in model HCM2) than when it is explained only by its indicators (as in model HCM1). In addition, the parameters in the SM were almost identical, hence the intention estimated based on the TPB better captured the behaviour than intention alone.

Table 3: Results of the DCM

Model	Scheduling model			HCM1			HCM2			HCM3		
Scheduling model	Values	t-test		values	t-test		values	t-test		values	t-test	
ASC (Early Dep)	-1.470	(-3.68)	***	-1.440	(-3.61)	***	-1.440	(-3.61)	***	-2.310	(-2.62)	**
ASC (Late Dep)	-0.604	(-1.64)		1.170	(1.67)		1.480	(2.06)	*	0.631	(0.70)	
β_{ETT}	-0.205	(-8.88)	***	-0.202	(-8.78)	***	-0.202	(-8.80)	***	-0.204	(-8.88)	***
β_{TC}	-0.156	(-9.28)	***	-0.154	(-9.20)	***	-0.154	(-9.21)	***	-0.155	(-9.22)	***
β_{ESDE}	-0.037	(-4.64)	***	-0.038	(-4.72)	***	-0.038	(-4.72)	***	-0.037	(-4.66)	***
β_{ESDL}	-0.088	(-9.17)	***	-0.088	(-9.12)	***	-0.088	(-9.14)	***	-0.089	(-9.32)	***
β_{DL}	-0.394	(-2.56)	*	-0.384	(-2.51)	*	-0.384	(-2.51)	*	-0.381	(-2.48)	*
St.dev (Early Dep)	-2.200	(-12.42)	***	-2.220	(-12.30)	***	-2.220	(-12.31)	***	-2.190	(-12.56)	***
St.dev (Late Dep)	-2.860	(-13.77)	***	-2.590	(-12.38)	***	-2.570	(-12.36)	***	-2.480	(-12.94)	***
Corr (Early-Late)	-1.600	(-6.32)	***	-1.510	(-5.01)	***	-1.510	(-5.04)	***	-1.410	(-5.39)	***
Latent variables Fixed working hours												
$\beta_{LV_ATT_time}$ (Early Dep)										0.047	(0.17)	
$\beta_{LV_ATT_time}$ (Late Dep)										0.320	(0.87)	
β_{LV_INT} (Late Dep)				-0.683	(-4.28)	***	-0.765	(-4.60)	***	-0.765	(-2.59)	**
β_{LV_PMN} (Late Dep)										-0.160	(-0.65)	
Latent variables Flexible working hours												
$\beta_{LV_ATT_time}$ (Early Dep)										0.451	(1.61)	
$\beta_{LV_ATT_time}$ (Late Dep)										0.817	(2.70)	**
β_{LV_INT} (Late Dep)				-0.322	(-2.07)	*	-0.416	(-2.49)	*	-0.425	(-2.14)	*
β_{LV_PMN} (Late Dep)										-0.445	(-2.55)	*
Summary												
Sample size:	2515			2515			2515			2515		
Number of draws:	1000			1000			1000			1000		
Null log-likelihood:	-2763.01			-2763.01			-2763.01			-2763.01		
Final log-likelihood:	-1791.042			-1774.349			-1773.171			-1762.385		
RHO ² for the null model:	0.352			0.358			0.358			0.362		
Adjusted RHO ² for the null model:	0.348			0.353			0.354			0.356		

Notes: Numbers in brackets represent the *t*-test statistics. **p* < .05; ***p* < .01; ****p* < .001.

In HCM3 we added perceived mobility necessities (PMN) and attitude towards short travel time (ATT_time) as additional latent constructs to intention (based on the TPB) to further increase the explanatory power of the model. We found that PMN were significant for the late departure. On the other hand ATT_time was significant for both early and late departures for individuals with flexible working hours, while not statistically significant (*p* < .05) for individuals with fixed working hours. This makes sense as individuals with flexible working hours are mainly concerned about being at work on time. All LVs have the expected sign: PMN is negative for late arrival, since individuals who have high perceived mobility needs are less likely to have room to reschedule. Similarly, ATT_time was positive, since individuals who find it important to have short travel times are more likely to reschedule their departure time in order to reduce travel time. It is also interesting how differently the LVs affect individuals with flexible and fixed working hours: ATT_Time and PMN are more important for individuals who have flexible working hours, while intention to be at work

on time is more important for individuals with fixed working hours, which is in line with our Hypothesis 4.

To test Hypotheses 1-3, we performed a likelihood ratio test (Ben-Akiva & Lerman, 1985) for all models against the basic SM and found that the model fit for all three models significantly improved ($p < .01$). Similarly, we compared the likelihood ratio test between model HCM2 and HCM3, and found that model HCM3 was also significantly better ($p < .01$). The likelihood ratio test can however only be used to compare nested models, hence we could not compare HCM1 with HCM2 and HCM3. However, comparing the adjusted RHO^2 values we saw that HCM3 was better than both HCM1 and HCM2. Thus, the results support our hypotheses.

6 Discussion and conclusions

In this paper we have shown that the understanding and modelling of departure time choice can be improved by the inclusion of relevant psychological factors into a DCM. For the selection of psychological factors we relied on the assumptions of the Theory of Planned Behaviour (TPB). We assumed three behavioural intentions to play a role for departure time choice: the intention to arrive on time; the intention to have short travel times; and the intention to have low travel costs. With regard to the intention to arrive at work on time, we estimated intention as determined by subjective norm, attitude, and PBC by structural equation modelling. When comparing the results of the structural equation model with results of studies in the context of mode choice, it is striking that PBC has a comparably small effect. Strong effects of PBC are, however, mostly found for PBC being a direct predictor of behaviour (e.g., Abrahamse et al., 2009; Haustein & Hunecke, 2007). The related behaviour in our context would, however, not be departure time choice but actually arriving at work on time, which was not considered in our model.

By including the intention to arrive at work on time as determined by social norm, attitude and PBC into a DCM, we could demonstrate that accounting for the TPB significantly improved the model estimation as compared to both a basic DCM without latent variables and a model including intention estimated solely by its own indicator variables. Being restricted by the length of the questionnaire, we did not include the full set of TPB-variables for the other two intentions but only attitude towards short travel time, which we deemed most important. The selection of psychological factors was completed by perceived mobility necessities, an extension of the TPB in the context of mode choice (Haustein & Hunecke, 2007), which we also expected to be relevant for departure time choice. As hypothesised both predictors became significant and further improved the prediction of departure time.

We additionally found that the specific effect of the different psychological variables depended on framework conditions, namely having flexible or fixed starting times at work. As expected, the intention to arrive at work on time had a stronger effect on people with fixed working hours. That the other psychological variables – PMN and ATT_Time – had a stronger effect for people with flexible time conditions can probably be explained by their better possibilities to reschedule, which allows them to be more open to the influence of other needs (or restrictions). With regard to the attitude towards short travel time, it would be interesting to learn more about what makes short travel times by car more or less attractive or important to individuals, especially to which extent this attitude is positively related to perceived mobility needs, and/or negatively related to affective motives of car use. For people who gain utility from driving, a significant reduction of their travel time is probably not a relevant motivation to reschedule their departure time, unless they perceive external pressure, e.g. in the form of high PMN. According to these considerations, attitude towards

travel time and PMN may be relevant variables to collect when designing targeted measures to stimulate changes in departure time choice in an individualised marketing approach.

In the case of perceived social pressure to arrive on time (subjective norm), interventions could be targeted at company managers aiming at changing the organizational culture towards more flexible arrival times, which may decrease attitude and subjective norm towards arriving at a specific time on the individual level. These examples, which are based on the modelling results we obtained, indicate that our results have important implications at a transportation demand management level, and that other strategies consisting solely in changing travel time and cost may be effective to shift departure time demand.

Future research could also focus on the inclusion of additional psychological factors that might be relevant for departure time choice. A key question here is what makes people more or less open to rescheduling their departure time. PMN in this study can be regarded as a proxy for this, as perceived mobility demand resulting from work and family responsibilities probably determine to which extent people are actually able to reschedule. Even if they are *able* to reschedule, this does not necessarily imply that they are also *willing* to do so. Therefore, the value orientation “openness to change” might be relevant to consider in future studies. Openness to change describes how people evaluate change and variation, and challenge and excitement as guiding principles in their lives. In a two-dimensional higher order value system it is regarded as the opponent of the value “conservation” (Schwartz, 1992). To our knowledge openness to change is the only value orientation that has been found to be related to transport behaviour when socio-demographic and other relevant variables are controlled for. People with high openness to change are found to have more trips, longer trips and as a result higher emissions/energy use resulting from their travel (Böhler et al., 2006; Hunecke et al., 2010; Poortinga et al., 2004). People with high PMN also travel more but trips may underlie a different motivation and fall less often into the leisure category. It would be interesting to see if people with a higher openness to change are actually more open to rescheduling and to which extent their higher engagement in activities works against this.

This study represents the first attempt to fully explore the effect of latent psychological behaviour in the departure time choice. The psychological items included in the questionnaire are derived from the authors’ theoretical discussions and considerations and from the application of the Theory of Planned Behaviour in the field of travel mode choice (e.g. Haustein & Hunecke, 2007). Before developing the items, it would have been very useful to have a qualitative phase including semi-structured interviews followed by a more extended pre-test to obtain precise and rich information about the majority of existing beliefs and their operationalisation. This might also have resulted in higher internal consistencies of the latent variables and is thus recommended for future work in this field.

The sample of this study can be regarded as a possible limitation as it cannot claim representativeness for car commuters. The most relevant difference between the sample and the population of car commuters in terms of the subject of our study is probably the higher percentage of people with flexible working hours included here. As we estimated the effects of the psychological factors for people with fixed working hours and flexible working hours separately, we do not see this as a problem for the interpretation of the effects of the psychological variables. It should, however, be taken into account when interpreting the results of the scheduling model part of the model.

Despite the existing limitations and the need for further research, we think that this work has demonstrated that both disciplines, microeconomics and psychology, can gain from each other and improve the understanding and modelling of departure time choice and thereby provide a better basis for changing departure time choice. While the focus of our paper was on car commuters, we think that similar considerations are also relevant for commuters using public transport and, in case of cycling cities, like Copenhagen, also for cycling. To which extent our results can be transferred to commuters using other modes remains a question for future research. As public transport service quality is strongly affected by overcrowded busses and trains and perceived safety by overcrowded cycling paths, designing flexible schemes for departure times appears relevant for all types of commuters.

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THE EFFECT OF PERCEIVED MOBILITY NECESSITY IN THE CHOICE OF DEPARTURE TIME

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ABSTRACT

Departure time choice plays a crucial role in addressing the problem of urban congestion. Since the work of Small (1982), many studies have shown that travelers trade-off between travel time and scheduling delay and that travel time variability also plays an important role because uncertainty is likely to affect the choice of departure time. However departure time choice is also related to the full daily activity pattern, such as a restriction or a preference in one activity may form restrictions in the flexibility of other activities and thereby affect the preference for the related departure time. In this paper we investigate how the latent effect of the *perceived mobility necessities* affects the choice of departure time. A stated choice experiment collected among workers who commute to Copenhagen center is used to estimate hybrid choice models where the discrete choice of departing before or later than the current trip depends on the latent construct of the *perceived mobility necessities*. Results show that individuals who perceive they have high mobility necessity tend to prefer the current departure time, and in particular dislike departing later. However the latent variables account also partially for panel effect across choice tasks.

1 INTRODUCTION

Urban congestion still represents one of the most relevant problems of the modern societies. According to The Forum of Municipalities (1) within the Greater Copenhagen Area (GCA) the traffic volumes have increased by more than 10% annually the recent years. In addition, that study revealed that congestion in the GCA have caused the average speed below 20 km/h on some parts of the road network, hence leading to more than 130.000 hours (i.e. 6 billion Danish Crowns, approximately 1 billion USD) are wasted daily. Copenhagen, like many other cities, is facing congestion problems on the roads. The departure time is the most important travel dimensions among several factors that play a role in traffic congestion. A number of studies have shown that people are more likely to change their departure time to address the problem of congestion rather than changing mode (2, 3, 4, 5) or even less change work and residential location. Although there are already evidences on departure time choices, as highlighted in Ortúzar et al. (6), more research is still needed.

One of the most used methods to study departure time choices is the Scheduling Model (SM) originally formulated by Small (7). The basic concept of the SM is that travelers who choose to reschedule their departure time to avoid congestion (and thereby experience the benefit of a shorter travel time) will experience a delay “penalty” by arriving later or earlier at the destination compared to their preferred arrival time. Later works included also travel time reliability (8, 9, 10, 11) that accounts for uncertainty about the actual travel time along a journey (i.e. the unexpected delay). In the literature (e.g. (12)) this concept is often referred to as travel time variability (TTV). It is important to include uncertainty because people who are risk averse might re-think their departure time choice in the presence of travel time variability.

Several evidences in the psychological literature showed that individual preferences for specific attributes and for specific alternatives are affected by individual attitudes and perceptions. Changing departure time implies either arriving late (even though slightly) or arriving much ahead to avoid the risk of being late. At the same time, departure time choice is also related to the full daily activity pattern, such as a restriction or a preference for one activity may form restrictions in the flexibility of other activities and thereby affect the preference for the related departure time. We envisage that the individual’s mobility necessity and more importantly how individual perceived their mobility necessity would play an important role in shaping individual preferences. Perceived mobility necessity (PMN) is defined as people’s perception of mobility as a consequences of their personal living circumstances. Researches in psychology showed that PMN has a significant effect on travel mode intention (e.g. (13)), but they use only an attitudinal approach. The transport literature reports several examples of the effect of attitudes and perceptions in the discrete choice, but to the best of our knowledge Arellana et al. (10) are the only ones who measure individuals’ attitude in the context of departure time. But none studied the effect of the perceived mobility necessity.

The objective of this paper is to study the effect of individual perceived mobility necessity in the preference for departure time. Furthermore, understanding this specific latent effect is an important step towards understanding the role of the full theory of planned behavior in relation to departure time choice.

Data were specifically collected for the purpose of this study. The sample consists of workers who commute during the morning peak in the metropolitan area of Copenhagen. The survey included a stated preference experiment customized on the real trips declared by the respondents in a trips diary, detailed information about the flexibility of the trips and a full set of questions to measure latent behavior as in the theory of planned behavior, plus socioeconomic information. This data are used to estimate hybrid choice models where the scheduling model is integrated by the latent variable model to account for the effect of no perfectly rational behavior in the preference for rescheduling the departure time.

The paper is structured as follows: Section 2 describes the data collection; Section 3 reports a brief review of the scheduling model and then its extension to account for the latent effect of perceived mobility necessity. Section 4 discusses the results of the model estimations and Section 5 reports the conclusions.

2 DATA COLLECTION

The data used in this research are specifically collected to study the departure time of workers who live in the suburbs and work in the city center in the metropolitan area of Copenhagen. The choice of focusing only on the trips toward the city center is motivated by the specific structure of the mobility in Copenhagen, where congestion is most dense in the rush hours along the main roads in both the inner and outer parts of the metropolitan area. The choice of focusing on morning commuting trips to work is instead quite typical in the studies on departure time because most of the trips in rush hours are commuting trips.

The overall structure of the survey designed for this study was organized in six parts. Individuals were presented with:

1) **An introduction and some initial questions.**

Initial questions, regarding main occupation, living and work location were needed to filter the target sample and to customize the trip diary and the stated choice experiment. The preferred arrival time was also asked as an initial question, as this is a fundamental prerequisite for the stated choice experiment.

2) **A full trip/activity diary.**

The trip diary was used to collect the characteristics (travel time, mode, purpose and so on) of all the trips/activities conducted within a 24-hour period (starting and ending at 3 a.m.). The diary was very detailed because it was linked to the Danish National Travel Survey (14, 15). Individuals were asked to describe the trips made the day before the interview.

3) **The stated preference experiments.**

The SP-game was presented as a part of the trip diary; hence as soon as a working trip was registered in the trip diary the respondent was presented with a series of hypothetical choice situations. The questionnaire was designed in this way in order to present the choice situation as early as possible, and avoid fatigue among the respondent when dealing with the complex trade-offs in the SP-games.

The SP experiment was built using an efficient design where individuals are asked to choose among three alternative departure time. The options were customized based on the trips described by each individual in the trip diary and on the departure time needed in order to be at work at their preferred arrival time (as revealed in part 1)). The efficient design was used because it allows using smaller samples. However, using an efficient design for the departure time is challenging. The major problem is that in the departure time studies, attributes are interdependent and the design attributes presented to the respondents differ from those in the model, by which the design is created (16), and this makes building the SP experiment quite difficult. Arellana et al. (10) are the only example of efficient design, but they use a two-step procedure that breaks the efficiency. In our study we were able to build a full efficient design because we pivoted around the preferred arrival for each individual instead of around the actual departure time. The two methods are proved to be equivalent as long as both the PAT and the actual trip are inside the rush hours (17). We restricted our sample to only include people who did go to work within the rush hours.

Another challenge related to the SP is the need to customize the experiment specifically for each individual in order to guarantee realism. Customize the SP for each individual is not possible with efficient designs, unless the real trips are known before optimizing the SP design. Six different designs were then constructed based on predefined travel times (10, 20, 30, 40, 50, and 60 minutes). Respondents were presented with the design which was closest to their reported travel time in the trip diary. This approach was necessary in order to ensure a reasonable level of realism for each respondent.

The attributes included in the SP experiments are departure time, travel time, travel cost and travel time variability. Each attributes has 3 levels, except travel cost which has 4 levels. Following the approach in Arellana et al. (10), the travel time variability was included as an unexpected delay once a week. In particular we defined the TTV as the TT that individuals experience once a week, hence with a 20% probability. The efficient design was constructed using the software package Ngene (18).

4) **Detailed questions about the flexibility of each trip reported in the diary.**

It is common in departure time survey to ask general questions regarding the flexibility of work. However departure time choice is (often) related to the full daily activity pattern, such as a restriction or a preference in one activity may form restrictions in the flexibility of other activities and thereby affect the preference for the related departure time. For this reason we decided to ask detailed questions that allowed us to fully understand the degree of flexibility of each activity. In particular we asked if the individual could have changed departure time earlier or later, have realized the activity in another location, another time of the day, another day or completely cancelled the activity. We also asked whether someone else could have done the activity for them and if they decided themselves what time to do the trip. Finally questions related to the frequency of each trip were also asked.

5) **A set of questions to define the construct in the theory of the planned behavior.**

In order to study the effect that psychological constructs have on the discrete choice of departure time, a set of 24 statements was presented to respondents that allow building all the constructs of the theory of planned behavior (TPB) (19). In particular, these statements allowed us to define: attitude toward being late, attitude toward flexibility in the activity schedule, attitude toward reducing travel time, subjective norm, personal norm, perceived behavioral control, intention not to being late, and perceived mobility necessities. Each of these latent construct are defined by a set of three statements. A 5-point Likert scale was used to measure the level of agreement to each statement. Arellana et al. (10) are the only example of departure time study that also includes attitudinal questions. We extended their work to account for the full TPB. However, as stated previously, this paper focuses on the latent construct of perceived mobility necessities.

6) **Socio-demographic information about the respondent.**

Finally, the survey is rounded off with a series of personal question capturing socio-economic background variables of each individual. Some descriptive analysis is shown in table 1. As we can see the sample is evenly distributed in terms of gender, age and household type, while there are a high percentage of individuals with high education and flexible working hours. The reason for this skewness is due to the fact that data was partially collected at University of Copenhagen and Copenhagen Business School, which are both located in the city center of Copenhagen. Another effect is that income is slightly higher than the general average of Greater Copenhagen Area, see table 1.

The sample was collected through two main sources: 1) an internet panel and, 2) by contacting companies and organizations. The data collection is still in progress. The main advantages of using a web based questionnaire is that 1) it allows to easily constructing customized questionnaires (which is important due to realism) with conditional questions for each respondent based on their specific trips and socioeconomic characteristic, 2) the cost per interview is relatively small, which allows for a larger sample size with limited resources, 3) it allows to define a set of criteria to be fulfilled by the people within the internet panel, and in that way ensure that only people who is in our target sample is present in the final sample, 4) it allows respondents to answer the questionnaire when they have time, thus a higher answer-rate. The disadvantage is that some groups of society (who do not use computers, e.g. kids and elderly people) are not present in the survey. However, since this study is limited to work trips in the rush hours, neither kids nor elderly people will be in the target group.

Only people who fulfill a number of carefully defined requirements were asked to complete the questionnaire. The requirements are: 1) being between 18-70 years old, 2) working in the city center of Copenhagen 3) going to work by car, 4) experiencing congestion or queue on the way to work, and 5) arriving at work between 7-9 a.m.

TABLE 1 Descriptive statistics of the sample

Sample		Current data	Danish National Travel Survey (TU)		
Area		Greater Copenhagen Area		Nationwide	
Main occupation		Worker		All occupations	
Individuals		293	34,791	76,789	109,583
Gender	Male	48.5%	48.8%	48.4%	48.1%
	Female	51.5%	51.2%	51.6%	51.9%
Age	0-17	0.0%	0.2%	13.0%	12.7%
	18-29	3.4%	10.2%	12.8%	13.2%
	30-39	20.8%	23.2%	13.3%	14.0%
	40-49	26.6%	30.1%	17.0%	17.0%
	50-59	31.7%	27.9%	16.5%	16.0%
	60-69	16.4%	8.2%	15.7%	15.5%
	70+	1.0%	0.1%	11.7%	11.5%
Household type	Single	11.3%	12.7%	16.5%	18.0%
	Single with child/children	6.1%	4.7%	5.9%	6.2%
	Couple	31.7%	31.7%	35.1%	34.0%
	Couple with child/children	50.9%	50.8%	42.3%	41.6%
	Unknown/other	0.0%	0.1%	0.1%	0.1%
Education	Elementary	0.7%	11.2%	31.5%	29.3%
	High school	0.7%	8.3%	7.9%	8.5%
	University	94.9%	46.1%	31.3%	35.1%
	Other/unknown	3.8%	34.4%	29.4%	27.1%
Work Type	Fixed	36.2%	77.2%	22.4%	21.8%
	Flex	62.1%	22.8%	6.6%	8.0%
	Unemployeed/unknown	1.7%	0.0%	71.1%	70.2%
Work hours p. week	Less than 37 hours	8.2%	25.7%	62.4%	61.4%
	37 hours	25.6%	54.7%	25.5%	25.7%
	More than 37 hours	66.2%	19.6%	12.1%	13.0%
Resp income	0-99	1.0%	1.1%	14.4%	14.2%
	100-199	1.0%	3.7%	15.4%	14.5%
	200-299	4.1%	0.6%	0.6%	14.3%
	300-399	16.7%	24.3%	15.4%	16.7%
	400-499	18.1%	32.1%	16.8%	7.4%
	500-599	17.7%	13.1%	6.8%	3.3%
	600-699	9.6%	5.0%	2.7%	1.9%
	700-799	11.3%	2.4%	1.4%	0.9%
	800-899	7.2%	1.2%	0.7%	0.5%
	900-999	6.1%	0.6%	0.4%	0.3%
	1000 or more	7.2%	0.3%	0.2%	0.8%
	Unknown	0.0%	15.5%	25.3%	25.2%

3 MODELLING PREFERENCE AND ATTITUDE IN THE DEPARTURE TIME

3.1 The scheduling delay model

The scheduling model (SM), as first formulated by Small (7), is based on the concept of trade-off between travel time and penalties for rescheduling, i.e. being early or late. The scheduling model assumes that travelers are faced with a discrete number of alternative departure times and they choose according to the following utility specification:

$$V_{jnt} = ASC_j + \beta_{TT} \cdot TT_{jnt}(DT_{jnt}) + \beta_{TC} \cdot TC_{jnt}(DT_{jnt}) + \beta_{SDE} \cdot SDE_{jnt} + \beta_{SDL} \cdot SDL_{jnt} \quad (1)$$

Where V_{jnt} is the utility for individual n associated to alternative j , in choice task t . TT is the total travel time from origin to destination, which in principle is a function of the departure time (DT), hence the notation $TT_{jnt}(DT_{jnt})$. Similar TC is the travel cost with respect to DT , while SDE and SDL are the scheduling delays, i.e. the cost of arriving early or late, respectively, and are defined as:

$$SDE_{jnt} = \max(-SD_{jnt}; 0) \text{ and} \quad (2)$$

$$SDL_{jnt} = \max(0; SD_{jnt}) \quad (3)$$

The Schedule Delay (SD) is defined as the difference between the Preferred Arrival Time (PAT) and the actual Arrival Time (AT) of alternative j , and AT must be equal to the departure time plus the total travel time, i.e. the SD for alternative j , individual n and choice task t is defined as:

$$SD_{jnt} = AT_{jnt} - PAT = DT_{jnt} + TT_{jnt} - PAT \quad (4)$$

If a traveler arrives at his or her preferred arrival time then SDE and SDL will be equal to zero. This yields that the individual will not experience disutility from rescheduling. However, TT is not constant, and it consists of different parts, as stated in Fosgerau et al. (12):

$$Travel\ Time = free\ flow\ time + systematic\ delay + unexplained\ delay \quad (5)$$

An extension of the scheduling model acknowledged the fact that travel time variability (TTV) plays a role in the choice of departure time. Based on the literature travel time variability have been included in two distinct ways: 1) Expected travel time, and 2) mean variance. However, some authors (20, 21, 22) recommend using the approach of expected travel time. Hence in this study the travel time variability is included as the expected travel time, $E(TT)$. Given a series of I different travel times for each alternative j and choice situation t , the expected travel time is the sum of the travel weighted by the probability (p_i) that each travel time occurs:

$$E(TT_{jnt}) = \sum_{i=1}^I p_i \cdot TT_{jnti} \quad (6)$$

And equations (2) and (3) will be written as:

$$E(SDE_{jnt}) = \sum_{i=1}^I p_i \cdot SDE_{jnti} = \max(-DT_{jnt} + E(TT_{jnt}) - PAT; 0) \quad (7)$$

$$E(SDL_{jnt}) = \sum_{i=1}^I p_i \cdot SDL_{jnti} = \max(0; DT_{jnt} + E(TT_{jnt}) - PAT) \quad (8)$$

Note that $\sum_{i=1}^I p_i = 1$.

3.2 The scheduling delay model with latent effect of perceived mobility necessity

Following the scheduling delay described in the previous section, our model specification takes the following form:

$$U_{jnt} = ASC_j + \beta_{TT} \cdot E(TT_{jnt}) + \beta_{TC} \cdot TC_{jnt} + \beta_{SDE} \cdot E(SDE_{jnt}) + \beta_{SDL} \cdot E(SDL_{jnt}) + \beta_{jAtt} \cdot PMN_n + \mu_{jn} + \varepsilon_{jnt} \quad (9)$$

Where all the terms have the same meaning as described in the previous section, while PMN_n is the latent variable that measure the individual perceived mobility necessity and μ_{jn} are random terms, normally distributed, that account for correlation among choice situations in the SP experiment.

According to the theory of the hybrid choice model (23, 24) the latent variable is defined as:

$$PMN_n = \alpha + \lambda \cdot S_n + \omega_n \quad (10)$$

Where S_n is a vector of individual socio-economic (SE) characteristics; λ is a vector of coefficients associated with these background characteristics, α is the constant and ω_n is a normal distributed error term with zero mean and standard deviation σ_ω .

The measurement equation of the latent variable is given by a set of K indicators according to the following expression:

$$IND_{kn} = \delta_k + \theta_k Att_n + v_{kn} \quad v_{kq} \approx D(0, \sigma_{v_k}^2), k=1, \dots, K \quad (11)$$

For identification purpose, it was set $\delta_1=0$ and $\theta_1=1$, all the other coefficients were estimated.

As the latent variable is associated with each individual n and does not vary among the SP choice set, then the unconditional joint probability is the integral of the SP conditional probability over the distribution of ω_n and μ_{jn} :

$$P_{jn} = \int_{\omega, \mu} \left[\prod_i P_{jnt}(\mu_{jn}, PMN(\omega_n)) \right] f(PMN | \omega_n) \left[\prod_k f_k(IND_{kn} | \omega_n) \right] f(\mu) f(\omega) d\mu d\omega \quad (11)$$

The log-likelihood function is given by the logarithm of the product of the unconditional probability:

$$LL = \sum_n \sum_j \log(P_{jn}) \quad (12)$$

The model was estimated using PythonBiogeme (25, 26).

4 MODEL RESULTS

This section discusses the results of the model estimations. Before estimating the models, data were checked to verify that all the individuals traded-off the attributes presented in the stated preference experiment when they evaluated the alternatives. The sample consists of 293 individuals, each answering 9 SP choices tasks. After a cleaning of the survey, 2574 observations were used for estimation. In the SP experiment, individual chose among 3 alternatives: departing at the current departure time (i.e. the one revealed by the respondent in the trip diary), departing earlier or departing later. Table 2 shows the results of the model estimated. For purpose of comparison the first two models are estimated using the scheduling model alone (i.e. estimated without latent variable). The first model is a multinomial logit (MNL) and does not account for panel correlation among the SP observations answered by the same individual n , while the second model is a mixed logit (ML) as it account for panel correlation. The last two models in Table 2 account for the effect of the *perceived mobility necessities* (PMN). Both are hybrid choice models, but model HCM does not account explicitly for panel correlation, while HCM-panel does.

Firstly we note that all coefficients in the scheduling model part are negative (as expected) for all the models estimated (with and without latent effect) and significant at more than 99.9%. Looking specifically at the value of the coefficients, we note that in all the specifications the penalty of arriving late is higher than the penalty of arriving early, i.e. $\beta_{E(SDL)} < \beta_{E(SDE)} < 0$. This is expected and similar findings can be found in numerous literatures (2, 5, 9, 10, 22, 27, 28, 29, 30, 31). Only very few studies (10, 32) does not support this trend. An interesting finding is that the marginal utility of $E(TT)$ is higher than both $E(SDE)$ and $E(SDL)$, hence the main priority for the respondents (in our sample) is the travel time, and less importantly, the scheduling delays. This is also supported by the descriptive statistics in table 1, which revealed that 62.1% of the respondent had flexible working start time. For respondents whose main priority is TT , they will be likely to select the early or late departure option to lower their TT . It is also interesting to note that this effect is also more evident when we account for correlation among choice task of the same individual (in the ML model).

Regarding the effect of the latent variable we first note that the statements we used as indicators of the latent *perceived mobility necessities* are the following:

- 1) The organization of my everyday life requires a high level of mobility.
- 2) I need to be mobile in order to solve my everyday duties.
- 3) My work requires a high level of mobility.

From the results of the hybrid choice model we first note that 2 of the 3 indicators used to reveal the latent effect of perceived mobility necessity are significant at more than 99.9% and positive. This is correct because the highest level of the 5-point likert scale indicating that individuals fully agree to the statements presented. We also note that the intercepts have a very low t-test (except for indicator 2 in the HCM without panel effect which is significant at more than 99.9%). This means that the estimated constants of the indicators in general have little influence, and the latent variable is instead explained mainly by the socio-economic variables in the structural equation.

The results from the HCM show that the latent variable in the alternative “departing earlier” is significant only at 50%, while the latent variable in the alternative “departing later” is significant at more than 99%. This indicates that individuals who perceived they have high levels of mobility needs are less likely to reschedule their trips, but they are particularly concerned about rescheduling later (the sign of the latent variable is negative in both alternatives, but it is significant only in the departure later alternative), and they rather prefer to stick with their current departure time. However it seems that the latent variables account also partially for panel effect across choice tasks, which is an expected effect, because the PMN depends on socioeconomic characteristics that are the same across choice tasks. When the HCM is estimated explicitly accounting for the panel effect, the significance of the latent variables change, significantly decreases for the alternative departing later, while increases (though still not significant at 95%) for the alternative departing earlier. The results have been found to be stable across multiple estimations using different socio-economic variables to explain the PMN in the structural equations.

TABLE 2 Model estimation results

Model	Scheduling model alone				Scheduling model with perceived mobility needs			
	MNL		ML		HCM		HCM panel	
Variable	Value	Robust t-test	Value	Robust t-test	Value	Robust t-test	Value	Robust t-test
<i>Scheduling model part</i>								
ASC DepCurrentTime	0.16	0.72	0.73	1.80	0.03	0.10	-0.77	-0.94
ASC DepLater	0.14	0.68	0.22	0.58	0.51	1.76	-0.02	-0.04
SIGMA DepEarlier			2.30	12.31			-2.27	-8.61
SIGMA DepCurrentTime			2.89	13.93			-2.79	-12.02
ETT	-0.09	-8.80	-0.20	-9.45	-0.09	-8.83	-0.21	-9.30
TC	-0.06	-6.44	-0.15	-8.46	-0.06	-6.43	-0.14	-8.24
ESDE	-0.03	-6.10	-0.04	-4.73	-0.03	-6.07	-0.04	-4.65
ESDL	-0.05	-11.04	-0.07	-9.13	-0.05	-11.01	-0.07	-8.98
PMN DepEarlier					-0.04	-0.72	-0.38	-1.51
PMN DepLater					-0.14	-2.55	-0.34	-1.52
<i>Latent variable (PMN) part</i>								
PMN constant					3.41	72.90	3.41	24.72
PMN sigma					0.04	1.76	0.04	0.59
Age 60-69					0.33	4.84	0.33	1.64
Age 70+					1.25	11.88	1.25	4.04
Low education					1.30	9.72	1.30	3.22
Children					0.15	2.92	0.15	0.98
Household Income					0.00	-9.01	0.00	-3.07
Indicator 1: St. dev.					-0.38	-12.00	-0.38	-4.06
Indicator 2: Intercept					-0.43	-4.17	-0.43	-1.41
PMN coeff.					1.05	37.35	1.05	12.68
St. dev.					-0.39	-9.41	-0.39	-3.17
Indicator 3: Intercept					-0.07	-0.89	-0.07	-0.32
PMN coeff.					0.89	38.10	0.89	13.01
St. dev.					-0.05	-2.38	-0.05	-0.83
Final log-likelihood:	-2437.7		-1864.5		-13745.7		-13188.8	
Rho adjusted (zero):	0.138		0.219		0.721		0.732	

Looking at the results in a more broad perspective, it is interesting that the findings in our study indicate that the latent variable capturing perceived mobility necessity does not directly have a significant (at 95%) influence on the departure time choice (when accounting for panel effect). Nevertheless, the signs of the latent variables are considered to be intuitive, since people who have a high perceived mobility need are likely to have many activities on the agenda (hence the high mobility need), and therefore cannot easily reschedule the activities. Hence, this indicate that perceived mobility necessities are indeed an important factor in departure time choice modeling, albeit more research are still needed. Also, based on the psychological literature, perception is believed to influence individual’s choices. This paves the road for more advanced models estimating a series of latent variables following the theory of planned behavior (TPB).

It is believed that a correct implementation of the latent construct from the TPB will have great policy implications, as this will close the gap between the research areas of engineers and psychologist, which both are explaining behavior, but in different ways. Hence, combining the two areas of research by including a set of underlying latent constructs in a HCM will be subject of further research.

5 CONCLUSION

In this paper we studied the problem of the departure time choice and in particular whether individuals' mobility needs and how they perceived it affects the preference for rescheduling the departure time. For this purpose we collected data using stated preference experiment to measure individual trade-offs between travel time and scheduling delay and travel time variability and we also collected information to measure the construct of the theory of the planned behavior. In particular we focused on the *perceived mobility necessities* and we studied its effect in the choice of departure time for morning commuters going to work in the morning rush hour.

We found that *perceived mobility necessities* indeed affect the choice of how to reschedule the departure time. Travelers who perceive they have high levels of mobility needs are less likely to reschedule their departure time, especially departing later, and they rather prefer to stick with their current departure time. These findings are believed to be reasonable, since people with (perceived) high mobility needs are likely to have a busy daily agenda, and therefore less willing – or able – to reschedule their activities, and thereby their trip timing. These findings are also interesting given the fact that they refer to people with a very high level of flexibility in terms of work starting and ending times. This makes it reasonable to believe that the findings in our study will be even stronger – and the latent variable more significant – given a representative sample of the population in Copenhagen, which in general will have a lower level of flexibility. Given the fact that data was partly collected at universities located inside Copenhagen, the sample include a large share of highly educated respondents and in general more flexible, and have a slightly higher income; hence making the sample not perfectly representative of the Danish population.

Our study are the first to capture the latent influence of perceived mobility necessities with respect to departure time models, and show that it is indeed relevant to extend the original theory of the scheduling model to incorporate effects that capture behaviors that depart from perfect rationality. However, the significance of the latent PMN is partly due to its role in accounting for the intra-individual correlation effect. This is an important result that needs always to be explored carefully as it has serious implications in terms of policy recommendations.

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The role of intention as mediator between latent effects and current behavior: application of a hybrid choice model to study departure time choices

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48 **Abstract**

49 An increasing number of papers are focusing on integrating psychological aspects into the typical discrete
50 choice models. The majority of these studies account for several latent effects, but they mainly focused on
51 attitudes, perception, and norms. In this paper we contribute to the literature in this field by accounting for
52 the full psychological effects as implied in the extended Theory of Planned Behavior. In particular, we study
53 the effect of the intention as mediator between the latent elements and the actual behavior, while attitude, the
54 social norms, and the perceived behavioral control affect the intention to behave in a given way. We apply a
55 Hybrid Choice Model to study the departure time choice. For this, we relied on data from Danish commuters
56 in the morning rush hours in the Greater Copenhagen Area. We found that accounting for the intention to
57 arrive at work on time is significant, and that the lower level mediators also had a significant influence on the
58 intention. Furthermore, the Attitude toward short travel time was also significant in deciding when to depart
59 for work. Finally, we tested how the hybrid choice model performed in some forecasting scenarios.

60

61

1 Introduction

During the past decade accounting for latent effects within discrete choices has gained increasing attention. Several studies in the transport field¹ have incorporated latent variables to better explain the discrete choice by capturing psychological constructs and have used the Hybrid Choice Model (HCM) framework (Ben-Akiva et al., 2002a; 2002b; 2012c) to estimate the joint effect of the latent variables in the discrete choice. The majorities of these studies focused on the effect of individuals' attitudes and mostly include only one latent effect at a time. There is also an increasing number of papers accounting for more than one single latent variable (Walker and Ben-Akiva, 2002; Johansson et al., 2006; Yáñez et al., 2010; Daly et al., 2012; Glerum et al., 2014; Bahamonde-Birke et al., 2014) but they focus only on attitudes and perceptions and only on their direct effect on the discrete choice.

Few papers focused on other effects beyond the attitude and perceptions. For example Cherchi et al. (2014) measured inertia in mode choice as a latent habitual effect using the frequency of the past trips as indicators. Thorhauge et al. (2014a) accounted for the effect of perceived mobility necessities in the choice of departure time. Tudela et al. (2011) measured the effect of expectation (attitude), affective (perception) and habit (attitude) in a mode choice context. Zhao (2009) studied the influence of six latent constructs (including personality traits, attitudes and perceptual factors) and provided one of the first evidences in the transportation literature of a HCM using a latent model structure where the latent variables affect the discrete choice directly, but also indirectly through the effect they have on other latent variables. Paulssen et al. (2014) estimated a simultaneous two-level hierarchical HCM with "values" at the lowest level of the psychological construct, affecting attitudes at a higher level, which ultimately affects the mode choice (see also Temme et al., 2008). Kamargianni et al. (2014) also incorporated a hierarchical relationship between two latent variables, albeit including two latent constructs.

None of the previous studies accounts for the mediating effect of intention to explain the effect of the latent construct in the actual behavior, as implied in the Theory of Planned Behavior (TPB). Thorhauge et al. (2015b) estimated the effect of the full TPB, as formulated originally by Ajzen (1991) and extended by Haustein and Hunecke (2007), to account also for the latent effect of perceived mobility necessity (PMN) in the choice of departure time. However, their main focus was on providing the theoretical background of the TPB in the departure time choice and to explain why it is essential to bring the TPB into the discrete choice of departure time. In their model, they used the sequential estimation, considered only the additive effect of intention and did not study the impact in prediction. In this paper we contribute to the literature in this field by accounting in the HCM for the full TPB effects. We extend the work of Thorhauge et al. (2015b) by (1) assuming that intention affects the marginal utility of the scheduling attributes and not only the preference for departing early/late, and that attitude toward short travel time and perceived mobility necessity affects the marginal utility of travel time, (2) exploring the role of objective constraints in the perceived control, (3) using a simultaneous estimation approach, and (4) testing the impact of accounting for all these effects in prediction.

Departure time is a crucial problem that has so far been studied almost exclusively from a microeconomic perspective, assuming that individuals make a rational choice based on the tradeoff between travel time, departure time and the scheduling delay (early or late) with respect to their preferred arrival time at the destination. One of the most popular methods is the Scheduling Model (SM) originally formulated by Small (1982). The basic concept of the SM is that travelers who choose to reschedule their departure time to avoid congestion (and thereby achieve shorter travel times) will experience a delay "penalty" by arriving later or earlier at the destination compared to their preferred arrival time. Within departure time choices, Arellana (2012) is the only one who accounted for the direct influence of individuals' attitude in a departure time context.

¹ There are several interesting studies in other fields than transport, but we chose to focus only on the transport literature as it provides sufficient evidence for the objective of this paper.

112 The policy implication of accounting for latent psychological effects is still an open research question. There
113 is a limited, but interesting discussion in the literature regarding the effect of latent variables in forecasts
114 (Zhao, 2009; Yáñez et al. 2010; Paulsen et al. 2013). In most of the cases the latent variables provide
115 valuable information about the cognitive process underlying the formation of individual preferences for a
116 given alternative that could prove useful to the design of policies but it does not improve the fit of the model,
117 and does have a strong impact in forecast.

118
119 The objective of this paper consists in studying the role of intention to behave in a given way into the actual
120 observed behavior, where the full intention is explained by the full latent constructs implied in the TPB. The
121 theoretical framework is applied to study the case of the departure time choice and policy implications are
122 also discussed. The remaining part of the paper is structured as follows: Section 2 reports a discussion of the
123 methodological background that motivates the model structure used in this paper. Then it describes the
124 scheduling model and its extension to account for the latent effect of TPB. Section 3 describes the data
125 collection, and Section 4 discusses the results of the model estimations. Section 5 reports the conclusions.

126 **2 Model framework**

127 As discussed in the introduction, departure time decisions are affected by how individuals assess changes in
128 level-of-service attributes (such as travel time and scheduling delay) but also potentially by underlying
129 psychological elements (as described in the Theory of Planned Behavior). The general formulation that
130 accounts for both these effects typically includes two components: a multinomial discrete choice model and a
131 latent variable model. In our formulation, the discrete choice component is represented by the typical
132 scheduling model extended to allow the alternatives' utilities to depend on both observed and latent
133 characteristics of the alternatives and the decision makers. The latent variable part allows for the
134 operationalisation of the relationships among several latent constructs that determine the intention to behave
135 in a given way, as implied in the Theory of Planned Behavior. The latent variables themselves are assumed
136 to be measured by multiple indicators representing and to be explained by observed characteristics of the
137 individuals and by other unobserved latent effects.

138
139 The proposed model framework is illustrated in Figure 1. An extensive theoretical and empirical analysis has
140 been conducted in order to define the psychological determinants of the departure time choice (a thorough
141 discussion is reported in Thorhauge et al., 2015b). Consistently with the extended Theory of Planned
142 Behaviour, we postulated that the discrete choice to depart early/late is directly affected by three latent
143 effects: perceived mobility necessities (PMN), attitude toward short travel time as well as the intention (INT)
144 to arrive at work on time. At the same time intention is mediated by subjective norm (SN), attitude toward
145 being on time, and perceived behavioral control (PBC). From the factor analysis we found that personal
146 norms (PN) could be grouped with the attitude toward being on time and intention to be on time. Thus, we
147 did not expect to be able to identify all these three effects with our data.

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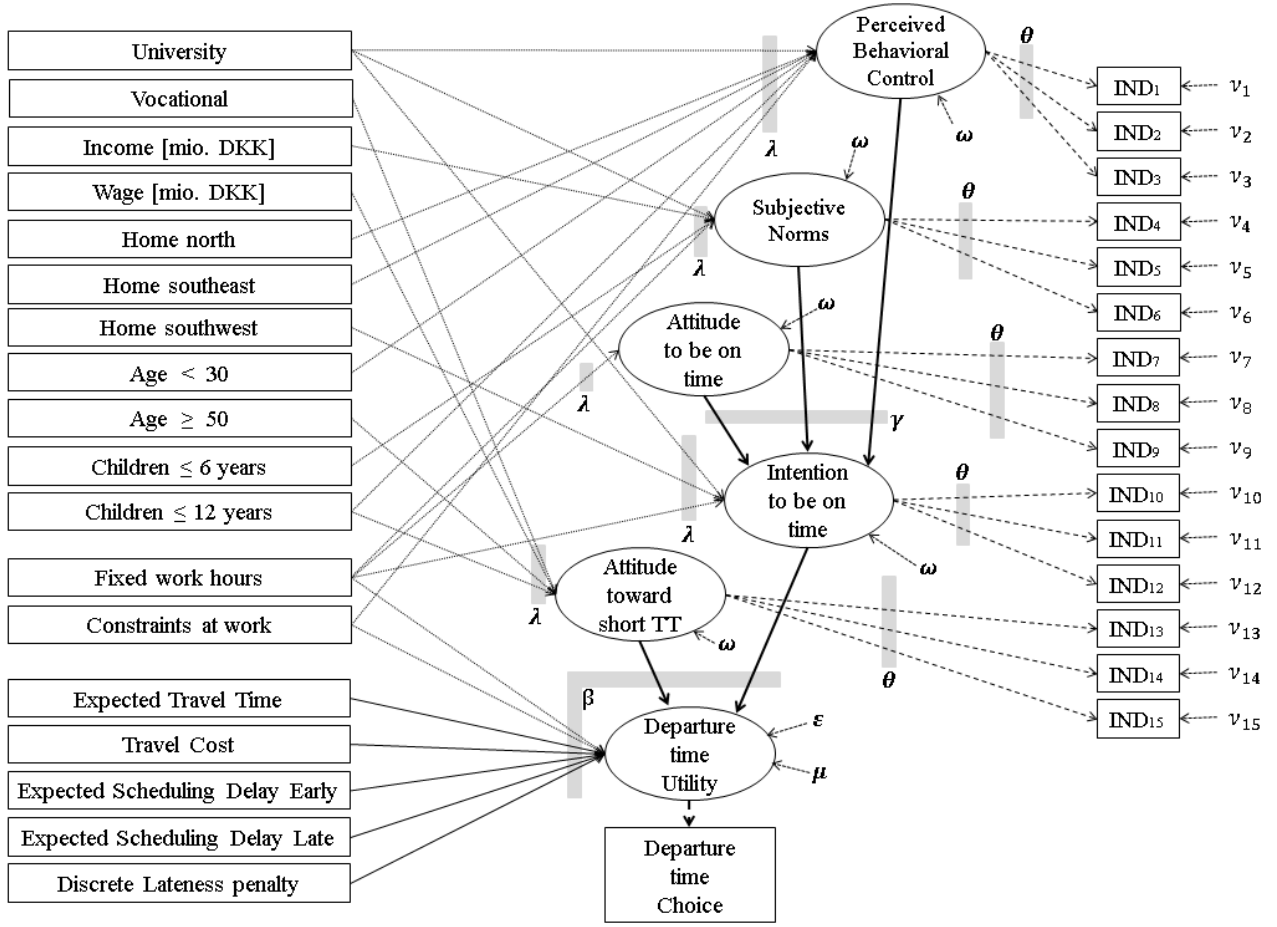


Figure 1 : Model structure accounting for the extended Theory of Planned Behavior.

We also postulate that intention to arrive on time does not affect simply the choice of the departure time but the individual's preference for arriving early or late because we expect that individuals who have a high intention to arrive at work on time will have a higher penalty from re-scheduling. Analogously, we expect that individuals who strongly value having a short travel time will have a higher penalty from travelling, while those who value high mobility are more likely to accept travel time. Hence we postulate that attitude toward short travel time and perceived mobility necessity both affect the marginal utility of travel time (in opposite directions).

Over the following subsections, we specify the functional form for the different components of the model framework. In the first subsection we describe the scheduling model typically used in the literature on departure, while in the second part we extend the specification to account for the psychological part capturing the latent variables.

2.1 The Scheduling Model

The basic concept of the Scheduling Model (SM), as originally formulated by Small (1982), is that individuals have a specific preferred arrival time (PAT), and choose their departure time (DT) making a trade-off between travel time (TT) and early (SDE) or late (SDL) scheduling delays (i.e. difference between the preferred and the actual arrival time). If a traveler arrives at his or hers preferred arrival time then the disutility from rescheduling will equal zero. Let $j = \{1, \dots, J\}$ be a set of mutually exclusive alternative departure times, $q = \{1, \dots, Q\}$ a sample of individual, and $t = \{1, \dots, T\}$ a set of repeated observations from

individual q (t can indicate choice tasks in a stated preferences experiment, or repeated observations in panel data. $t=1$ in case of cross-sectional data). The Scheduling Model is expressed as follows:

$$V(SM)_{jqt} = \beta_{TT} \cdot E(TT_{jqt}) + \beta_{TC} \cdot TC_{jqt} + \beta_{SDE} \cdot E(SDE_{jqt}) + \beta_{SDL} \cdot E(SDL_{jqt}) + \beta_{DL} \cdot DL_{jqt} \quad (1)$$

Where

- $V(SM)_{jqt}$ is the utility that individual q assigns to alternative j in the observation t .
- $E(TT_{jqt})$ is the expected travel time from origin to destination. This captures the travel time variability (TTV), and it is calculated as the sum of the travel time (TT_{jqti}) weighted by the probability (p_i) that each travel time occurs :

$$E(TT_{jqt}) = \sum_{i=1}^I p_i \cdot TT_{jqti} \quad (2)$$

with $i=\{1,...,I\}$ is a series of different travel times for each alternative j and observation t .

- TC_{jqt} is the travel cost from origin to destination.
- $E(SDE_{jqt})$ and $E(SDL_{jqt})$ are the scheduling delays, i.e. the disutility of arriving early or late. The scheduling delay is the difference between the preferred arrival time (PAT) and the actual arrival time (AT). Since the arrival time – and thereby the scheduling delays – are also affected by travel time variability, the scheduling delays are calculated, similar to the travel time, as:

$$E(SDE_{jqt}) = \sum_{i=1}^I p_i \cdot SDE_{jqti}; \quad E(SDL_{jqt}) = \sum_{i=1}^I p_i \cdot SDL_{jqti} \quad (3)$$

$$SDE_{jqti} = \max(-SD_{jqti}; 0); \quad SDL_{jqti} = \max(0; SD_{jqti}) \quad (4)$$

$$SD_{jqti} = AT_{jqti} - PAT \quad (5)$$

- DL_{jqt} is a dummy variable indicating a late penalty, defined as:

$$DL_{jqt} = \begin{cases} 1 & \text{if } E(SDL_{jqt}) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

2.2 The integrated Scheduling Model and Theory of Planned Behavior

To integrate the Theory of Planned Behavior into the Scheduling Model, we extend the specification of the systematic component of the utility, as reported in equation (1), allowing the latent constructs to affect the utility of the departure time directly (i.e. summed) and indirectly through the marginal utility of the attributes in the scheduling model. Moreover, in accordance with the random utility maximization theory we assume that the utility (U_{jqt}) that individual q assigns to the departure time alternative j in the observation t , is described by a systematic part, that is represented by the Scheduling Model extended to account for the psychological effects, of and some stochastic component. In accordance with framework reported in Ben-Akiva et al. (2002b), the utility of our hybrid choice model can be written as:

$$U_{jqt} = ASC_j + (\beta_j^{SM} + \beta_j^{SM \cdot LV} \cdot LV_q) \cdot LoS(SM)_{jqt} + \beta_j^{LV} \cdot LV_q + \mu_{jq} + \varepsilon_{jqt} \quad (7)$$

Where

- ASC_j is the alternative specific constant for alternative j .

- $\mathbf{LoS}(\mathbf{SM})_{jqt} = \{\mathbf{E}(\mathbf{TT}), \mathbf{E}(\mathbf{SDE}), \mathbf{E}(\mathbf{SDL}), \mathbf{TC}, \mathbf{DL}\}$ is a vector of level-of-service characteristics, as included in the systematic utility of the scheduling model.
- \mathbf{LV}_q is a vector of M latent variables measuring the latent psychological effect of individual q .
- $\beta_j^{SM}, \beta_j^{SM \cdot LV}$ and β_j^{LV} are vectors of coefficients that measure the marginal effect of the level-of-service attributes alone, as a function of the LV and the marginal effect of the LV.
- ε_{jqt} is a typical i.i.d. EV type 1 error term
- μ_{jq} are random terms, normally distributed, that account for correlation among repeated observations from the same individual.

The latent variables are defined by a set of M structural equations defined as:

$$LV_{qm} = \alpha_m + \lambda_{m,SE} \cdot \mathbf{SE}_q + \sum_{n \neq m} \gamma_n LV_{qn} + \omega_{qm} \quad \forall m, n \in M \quad (8)$$

Where

- LV_{qm} and LV_{qn} are the latent variables m and n for individual q .
- γ_n is a coefficient associated to the latent variable n that hierarchically affects the latent variable m .
- \mathbf{SE}_q is a vector of individual and family socio-economic characteristics and $\lambda_{m,SE}$ the corresponding vector of coefficients.
- α_m is the constant in the structural equation for latent variable m .
- ω_{qm} is a normally distributed error term for latent variable m with zero mean and covariance matrix Σ_ω .

The measurement equation of the latent departure time utility is defined as a standard discrete choice model where each latent variable is given by a set of R measurement equations, corresponding to the number of indicators for each LV. Given M latent variables we define a total of MR measurement equations according to the following expression:

$$IND_{qrm} = \delta_{rm} + \theta_{rm} \cdot LV_{qm} + v_{qrm} \quad \forall m \in M, r \in R \quad (9)$$

Where

- IND_{qrm} is the indicator r of the latent variable m for individual q
- θ_{rm} is a coefficient associated with IND_{qrm} , i.e. the parameter for indicator r latent variable m .
- δ_{rm} is the constant in the measurement equations for indicator r of the latent variable m .
- v_{qrm} is a normally distributed error term for latent variable m with zero mean and standard deviation σ_v .

Let Φ be the standard normal distribution function. Assuming independence among the LV (for simplicity), the distribution of the latent variable and the indicators are:

$$f_{LV_{qm}} = \frac{1}{\sigma_\omega} \Phi \left(\frac{LV_{qm} - (\alpha_m + \lambda_{m,SE} \cdot \mathbf{SE}_q + \sum_{n \neq m} \gamma_n LV_{qn})}{\sigma_\omega} \right) \quad \forall m \in M \quad (10)$$

$$f_{IND_{qrm}}(\omega) = \frac{1}{\sigma_{v_m}} \Phi \left(\frac{IND_{qrm} - (\delta_{rm} + \theta_{rm} \cdot LV_{qm}(\omega))}{\sigma_{v_m}} \right) \quad \forall m \in M, r \in R \quad (1)$$

For the purpose of theoretical identification, we defined $\delta_{1m}=0$ and $\theta_{1m}=1$. All the other coefficients are estimated. As the latent variables are associated with each individual q and do not vary among the SP choice set, then the unconditional joint probability is the integral of the SP conditional probability over the distribution of ω_n and μ_{jn} :

$$P_{jq} = \int_{\omega} \left(\int_{\mu} \prod_{t=1}^T P_{jq,t}(\mu_{jq,t}, \omega_q) f(\mu) d\mu \right) \prod_{m=1}^M f_{LV_{qm}}(\omega) \prod_{r=1}^R f_{INDrrm}(\omega_m) f(\omega) d\omega \quad (2)$$

The log-likelihood function is given by the logarithm of the product of the unconditional probability:

$$LL = \sum_q \sum_j \ln(P_{jq}) \quad (3)$$

The model was estimated using the software package PythonBiogeme (Bierlaire, 2003; Bierlaire and Fethiarison, 2009).

3 Data Collection

The data used in this study are specifically collected to study the departure time of workers who live in the suburbs and work in the city center in the metropolitan area of Copenhagen. The choice of focusing only on the trips toward the city center is motivated by the fact that congestion is more dense in the rush hours for people travelling into the city center, thus creating an incentive to (consider to) reschedule. On the other hand, the choice of focusing on morning commuting trips to work is quite typical in the studies on departure time because most of the trips in rush hours are commuting trips.

The questionnaire set-up to collect the data consists of six steps. Individuals were presented with:

- 1) **Initial questions** regarding main occupation, living and work locations, and preferred arrival time at work needed to filter the sample and to customize the trip diary and the stated choice experiment.
- 2) **A full trip/activity diary** to collect the characteristics (travel time, mode, purpose, etc.) of all the trips/activities conducted within a 24-hour period (usually the day before).
- 3) **Detailed questions about the flexibility of each trip reported in the diary**, to collect information on time, space and coupling (i.e. among people) constraints for all activities and trips described in the diary.
- 4) **A stated preference experiment** where individuals were asked to choose among three alternative departure time. Options were customized based on the trips described by each individual in the diary and on the departure time required to be at work at their preferred arrival time (as revealed in step 1). Each respondent were presented with 9 choice tasks. The attributes included in the SP experiments are departure time, travel time, travel cost and travel time variability, defined as travel time variability as the travel time individuals experience once a week, hence with a 20% probability. Details on the stated preference experiment can be found in Thorhauge et al. (2014b),
- 5) **A set of questions to define the construct in the TPB**. A set of 24 statements was presented to the respondents which allowed us to define the following constructs: attitude toward being on time, attitude toward flexibility in the activity schedule, attitude toward reducing travel time, subjective norm, personal norm, perceived behavioral control, intention to be at work on time, and perceived mobility necessities. A total of 8 latent constructs were defined in accordance with the TPB by a set of 3 statements each. A confirmatory factor analysis was then conducted to verify that the indicators were grouped as expected during the design phase. A detailed description of the analyses that allow defining the TPB structure for the departure time choice can be found in Thorhauge et al. (2015b).
- 6) **Socio-demographic information** about the respondent and her/his family such as age, profession, presence of children and age, income and so on.

The data was collected as a Computer Aided Personal Interview (CAPI) by sending e-mails to respondents in the target sample with a link to the survey. The sample was collected at different locations in central

296 Copenhagen. More than 10,000 questionnaires were distributed via e-mail. A total of 2,369 replies were
297 obtained, but after carefully cleaning the data, the final sample consists of 286 respondents. The data were
298 cleaned based on the requirement that individuals: 1) are between 18-70 years old, 2) work in the city center
299 of Copenhagen 3) go to work by car, and 4) arrive at work between 6-10 a.m. More details on the survey
300 questionnaire and data collection can be found in Thorhauge et al. (2015a).

301 **4 Results**

302 In this section we will discuss the results of the estimation of the hybrid choice models accounting for the
303 extended Theory of Planned Behavior. Table 1 reports the models' results. The estimation of a MNL without
304 psychological elements is also included for comparison reasons. Before estimating the model depicted in
305 Figure 1, simple models with only one LV each were estimated to define the socio-economic characteristics
306 that explain each latent construct. All the socio-economic characteristics included in the TPB were also
307 tested directly in the SM, i.e. interacting with the attributes of the scheduling model or summed. None of
308 them resulted significantly different from zero. This result is interesting as it reveals that the psychological
309 construct is what indeed explains heterogeneity in preference in our context.

310
311 In the remaining part of this section we will discuss the modeling results. Firstly, we will discuss the direct
312 predictors of the choice, then we will discuss the indirect predictors within the TPB, and finally, we will
313 discuss the socio-demographic variables in the structural equations of the LVs.

314
315 Regarding the departure time choice we see (Table 1) that in both models (SM-alone and HCM) all
316 coefficients are negative and are highly significant. In the HCM the scheduling variables, i.e. expected
317 scheduling delay, expected scheduling delay late and lateness Penalty - DL, interacts with the intention to be
318 at work on time. All parameters are negative, with the exception of DL for individuals without arrival time
319 constraint at work, which is however not significantly different from zero. This means that the penalty for
320 rescheduling is not influencing individuals without constraints at work, whereas for individuals with
321 constraints at work it increases with the intention to arrive at work on time. Furthermore, we found the
322 attitude toward short travel time to be statistically significant when interacted with the expected travel time.
323 The negative parameter is as expected; as it means that high attitude toward short travel time decreases the
324 marginal utility for the expected travel time. Finally, we also attempted to interact perceived mobility
325 necessity with the expected travel time, but that was not statistically significant, and it was not included in
326 the final model. We also tested the latent variables summed in the utility function, but less significant
327 parameter estimates were obtained.

328
329 Focusing on the lower level effects (i.e. the variables that affect intention), Table 1(b), we found attitude
330 toward being on time, subjective norms, and perceived behavioral control to be statistically significant as
331 mediators for intention. All parameters are positive, as expected, due to the direction of the indicator
332 statements. More specifically, if the respondents had a high agreement with attitude late, subjective norms,
333 and perceived behavioral control, they were also more likely to have a high agreement with the intention to
334 be at work on time.

335
336 Finally, we tested an extension of the TPB adding personal norms as a mediator for intention alongside
337 attitude toward being on time, subjective norms, and perceived behavioral control. We found that when
338 adding this latent variable to the TPB structure the other LVs would become unstable. More specifically we
339 found that attitude toward being on time and subjective norms decrease in magnitude (albeit they maintain
340 the same sign). The findings suggest that we could estimate either personal norms or attitude toward being
341 on time. This result was expected because, as mentioned before, in the factor analysis we found that personal
342 norms could be grouped with attitude toward being on time and intention. As the structure of TPB is already
343 firmly grounded in the literature, we chose to disregard personal norms for further analysis at this point.

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347 **Table 1(a):** Model estimates of Scheduling Model part.

Model	Scheduling Model alone (M1)		Hybrid Choice Model (M2)	
	With Panel Effect		With Panel Effect	
Work Hours	Flexible	Fixed	Flexible	Fixed
Travel cost -TC	-0.188 (-9.49)	-0.094 (-4.79)	-0.182 (-9.52)	-0.083 (-3.69)
Expected travel time -E(TT)	-0.239 (-9.05)	-0.128 (-4.57)		
E(TT) * Attitude toward short travel time			-0.061 (-8.86)	-0.031 (-3.54)
Constraints at work	No constraints	Constraints	No constraints	Constraints
Expected scheduling delay late -E(SDL)	-0.069 (-6.65)	-0.114 (-8.32)		
E(SDL) * Intention			-0.017 (-6.94)	-0.027 (-7.39)
Discrete lateness penalty (DL)	-0.003 (-0.01)	-0.666 (-3.15)		
DL * Intention			0.011 -0.21	-0.148 (-2.83)
Generic parameters	All individuals		All individuals	
Expected scheduling delay early -E(SDE)	-0.04 (-4.9)			
E(SDE) * Intention			-0.009 (-4.98)	
ASC (Early Departure)	-1.26 (-3.06)		-1.25 (-3.15)	
ASC (Late Departure)	-0.517 (-1.41)		-0.529 (-1.41)	
St.dev (Early Departure)	-2.27 (-11.83)		2.27 -11.66	
St.dev (Late Departure)	-2.58 (-12.55)		2.62 -9.38	
Corr (Early- Departure)	-1.54 (-5.27)		1.67 -3.03	
Model Summary				
# draws	1000		1000	
Sample size:	2515		2515	
Final log-likelihood:	-1753.947		-7464.797	

348

Table 1(b): Model estimates of the latent variable part.

Model		Hybrid Choice Model With panel (M2)				
Variable		Attitude toward short travel time	Intention to be on time	Attitude toward being on time	Subjective norms	Perceived behavioral control
Structural equations						
Constant		3.62	1.04	3.73	3.61	4.63
		-32.05	-1.84	-40.86	-16.35	-27.65
Sigma		-0.359	-0.793	-0.093	0.093	-0.472
		(-3.24)	(-3.49)	(-1.55)	-1.13	(-3.85)
Constraints at work						-0.303
						(-2.43)
Fixed work hours			-0.091	0.917	1.05	
			(-1.01)	-6.92	-5.84	
Education at university level			-0.187		-0.81	-0.297
			(-2.05)		(-3.98)	(-1.91)
Vocational education		-0.305				
		(-1.77)				
Income [million DDK]					0.43	
					-1.19	
Wage [million DDK]		9.7				
		-2.5				
Home north of CPH						0.167
						-0.88
Home southeast of CPH						-0.213
						(-1.23)
Home southwest of CPH			-0.162			
			(-1.4)			
Age < 30						-0.526
						(-1.5)
Age ≥ 50		-0.106				
		(-0.85)				
Presence of children ≤ 6 years old					-0.389	
					(-2.37)	
Presence of children ≤ 12 years old		0.196				-0.208
		-1.62				(-1.71)
LV: Attitude toward being on time			0.487			
			(-5.53)			
LV: Subjective norms			0.187			
			(-3.32)			
LV: Perceived behavioral control			0.235			
			(-2.64)			
Measurement equations						
Indicator 1:	St. dev	-0.164	-0.667	-0.542	-0.405	-0.351
		(-1.97)	(-5.11)	(-4.26)	(-1.97)	(-2.86)
Indicator 2:	Intercept	-0.298	-0.199	-0.68	0.03	0.128
		(-0.66)	(-0.54)	(-2.29)	-0.09	-0.21
	LV coeff.	1.02	0.941	1.09	1	0.978
		-8.23	-11.48	-15.9	-10.28	-6.49
	St. dev	-0.025	-0.106	-0.338	-0.316	-0.133
		(-0.38)	(-1.55)	(-4.83)	(-2.19)	(-1.32)
Indicator 3:	Intercept	1.11	-0.59	-0.475	0.744	1.65
		-2.07	(-1.71)	(-1.5)	-2.78	-2.56
	LV coeff.	0.858	1.12	1.01	0.763	0.697
		-6.06	-15.23	-13.43	-9.65	-4.57
	St. dev	-0.338	-0.756	-0.09	-0.047	-0.519
		(-3.16)	(-4.96)	(-1.21)	(-0.67)	(-4.47)

Turning our attention to the remaining socio-demographic variables in the structural equations of the latent variables, (b), we found that having an academic education decreases the subjective norms, perceived behavioral control and not least the intention to be at work on time; thus the rescheduling penalty is lower for these individuals. This is reasonable due to the type of jobs possessed by highly educated individuals, but also to a general state of mind and analytic skills, as they are likely to be less driven by what other people think about them. Individuals' attitude toward short travel time decreases for individuals with vocational education, which results in a lower likelihood of rescheduling their departure time, and increases with the wage rate, which means that the higher the income per hour worked, the more likely individuals are to reschedule their departure time in order to decrease their travel time. This is intuitive as typically high wage rates lead to high value of travel time. Income is also positively correlated with the social norm (toward being at work on time). Hence, individuals who have high income because they have high wage rates are compelled by two effects that can go in opposite directions: fulfilling peers' expectation of being on time and reducing travel time.

The presence of children under 6 and 12 years of age, influences negatively the subjective norms and perceived behavioral control toward being on time at work. This means that the presence of pre-teenagers in the household make it less likely that the respondents will depart in order to arrive at work on time. Due to household obligations, such as escorting trips in the morning, individuals deprioritize their own obligations and preferences (e.g. at work). Furthermore, in line with the findings for subjective norms and perceived behavioral control, the presence of children below 12 years of age increases individuals' attitude toward having a short travel time, which makes the respondents more likely to reschedule.

Last but not least we tested the effect of flexibility constraints. We found that subjective norms and attitude toward being on time at work increases if the respondents have fixed work hours. This means that the intention to be at work on time increases if the respondents have fixed work hours and thus a higher penalty of rescheduling. However, the parameter for having fixed work hours is negative for intention, which is counterintuitive, as it indicates that individuals with fixed work hours are more likely to reschedule. This happens because of the inclusion of the three underlying latent variables explaining intention. More specifically, when estimating the model without any lower level LVs the parameter for having fixed work hours is – as expected – positive. Furthermore, even when estimating the model with any one of the lower level LVs separately, the parameter remains positive. However, when including all three lower level LVs (and interact intention with the scheduling variables), the data do not allow to correctly estimating the parameter for fixed work hours, and it becomes insignificant.

In line with the psychological theory, we also tested the effect of the objective constraints in the perceived behavioral control. We focused on the temporal constraint because the TPB for this study is designed to capture the intention to be on time at work. We defined the temporal flexibility as the difference between the reported arrival of the respondents and their declared latest possible arrival time. We found that TPB is affected by objective temporal constraints if the flexibility is less than 10 minutes. Other buffer sizes were tested as well, however a 10 minute buffer was the only one being significant at 95%. This means that individuals who are facing constraints perceived that it is more difficult to fulfill this constraint, while flexible individuals are not faced with such a challenge. This finding relation would especially have made sense if perceived behavioral control also affects the choice directly (and not just through intention), which is in line with the theory. However, in our case, perceived behavioral control was not significant when influencing the choice directly (not even when the LV were estimated alone), but only through intention.

Finally, we note that when the model is estimated without panel effect, i.e. assuming all observations in the sample to be independent, all parameters are highly significant, which suggests that the effects we found are relevant, though more observations are probably needed to get more statistically robust results.

5 Forecasting

As a final step we tested the implications of using a HCM in some simple forecast scenarios. Before discussing the forecasting results, we analyzed the marginal effects of the latent constructs. Table 2 summarizes some characteristic of the intention and the attitude toward on time, as these are the two latent variables that directly affect the departure time utility. Figure 2 shows the marginal utility of the scheduling delays as a function of intention and attitude toward being on time for both the Scheduling Model and the Hybrid Choice Model. These are computed via simulation of the structural equations. More specifically, as the Scheduling Model does not account for psychologic items and it is not able to capture any variance in the preferences due to latent constructs (the lines are horizontal). However, accounting for psychological items allows capturing differences in preferences among individuals. As expected the intention to be on time is higher for individuals with constraints on how late they can arrive at work than individuals without constraints, and this has a clear impact on the marginal utility of the scheduling delays. Even though the marginal utility of the SM-alone produces a similar average compared to the HCM, it does not allow capturing differences among individuals.

Table 2: Characteristics of the latent variables

Latent variable	Mean	Std. Dev	Min	Max
Intention to be on time	4.37	0.30	3.95	5.16
<i>Constraints at work</i>	4.52	0.31	3.95	5.16
<i>No Constraints at work</i>	4.24	0.21	3.96	4.86
Attitude toward short travel time	3.77	0.18	2.21	4.09
<i>Fixed working hours</i>	3.77	0.15	3.32	4.05
<i>Flex working hours</i>	3.79	0.15	3.29	4.05
Attitude toward being on time	4.03	0.43	3.73	4.64
Subjective norms	3.36	0.61	2.51	5.00
Percieved behavioral control	4.18	0.21	3.60	4.63

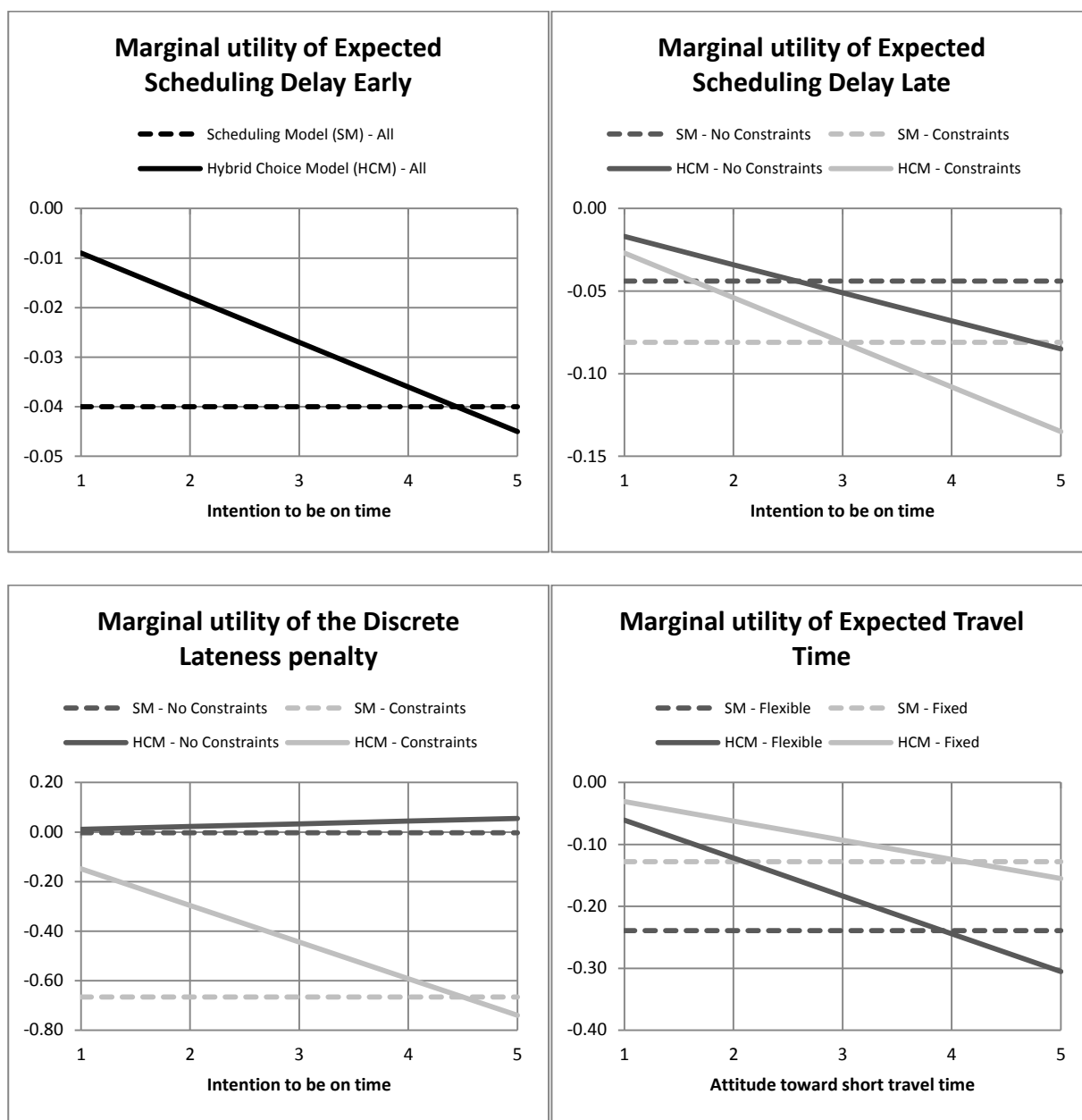
Following Yáñez et al. (2010) we tested two forecast scenarios. The first implies change in the *transport system*, i.e. the impact of introducing a toll ring around Copenhagen (Figure 3). Similarly to Thorhauge et al. (2015a), we assumed a charge of 20 DKK in the central peak period between 7:30-8:30, a charge of 10 DKK between 7:00-7:30 & 8:30-9:00 and no charge at the shoulders of the rush hours before 7:00 and after 9:00. In the second scenario we tested a change in the *activity system*, assuming all commuters to have flexible work hours (Figure 4). We are aware that such an assumption is unrealistic, but it is useful and interesting to study the performance of the HCM in such a forecast scenario.

For the forecast scenarios we defined 10 time periods consisting of 15 minutes' intervals between 7:00-9:00, and 1-hour periods between 6:00-7:00 and 9:00-10:00. The model estimated with the SP data was then calibrated to adjust constants and scale to the real departure times observed in the Danish National Travel survey. Details are reported in Thorhauge et al. (2015b).

When introducing a toll ring scenario we note how individuals shift away from the congestion charges in the peak hour. The number of individuals with flexible work hours who depart before 7:00 A.M. increases by 15%, while after 9:00 A.M. the increase is almost 20%. For individuals with fixed work hours, however, nearly none chooses a later departure time, while some chooses an earlier departure time as a response to the introduction of a toll ring. Result in Figure 4 show that assuming all individuals to have flexible work hours and no constraints at work does not change the overall departure time patterns much without also introducing a toll ring. However, when also introducing a toll ring, the respondents are given an incentive (i.e. to avoid the congestion charging). We note that forecasts from the HCM and SM without socio-demographics do not seem to be that different. This makes sense because the scenario is evaluating a change in the transport system that is adequately captured by both models. And since the inclusion of socio-demographic variables in the SM model was not found to be significant, their omission does not seem to have any perceptible effect on forecasts. This confirms some recent concerns about the benefit of using HCM in prediction.

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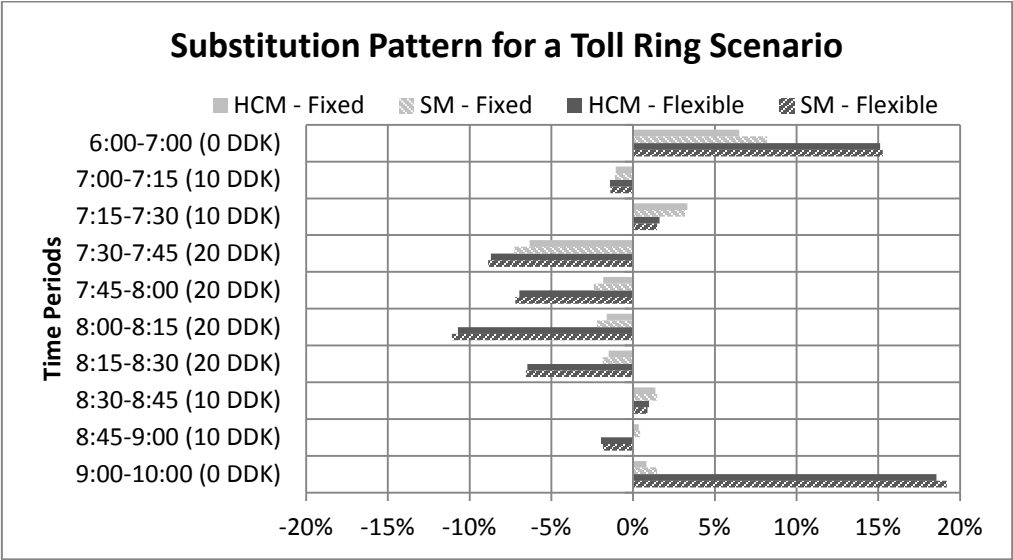
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Figure 2: Marginal utility of the Scheduling Model attributes.

452 Since the HCM allows capturing the effect of the socio-demographic variables, significant differences in
 453 forecasts are found if we look at the market shares for different groups of the sample (Figure 5). We found
 454 that when introducing a toll ring younger people (i.e. below 30) are more likely to reschedule, probably due
 455 to the fact that such individuals have fewer obligations. The elderly segment of the work force is instead less
 456 likely to reschedule, possibly because they tend to be more driven by habits. We also see that individuals
 457 with a university degree prefer to reschedule both earlier and later to avoid the congestion charging, possibly
 458 because these individuals are also more likely to be flexible, while individuals with vocational education
 459 only reschedule to an earlier departure time in order to avoid congestion charging.

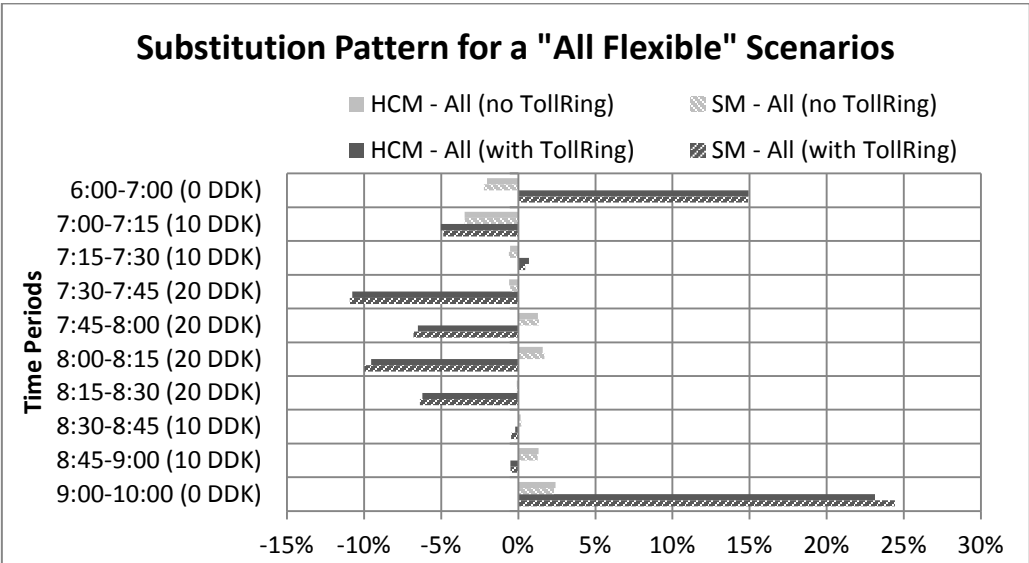
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 461 The major differences are registered between fixed and flexible individuals, and different segments in the
 462 sample, but both model structures (SM-alone and the HCM) predict similar changes. However, different
 463 substitution patterns are seen when segmenting on the level of intention to be at work on time. As seen in
 464 Table 2 all individuals agree on being at work on time (i.e. minimum level of intention is just below 4 on a 1

465 to 5 Likert scale), hence the segmentation is between individuals who *agrees* and *strongly agrees*. We
 466 divided the individuals into three segments with intention level equal to 4, 4.5, and 5, and computed the
 467 substitution pattern for each segment (Figure 6). When a toll ring is introduced, individuals who have a
 468 strong intention to be at work on time will not reschedule to a later departure time options, while individuals
 469 with a lower intention to be at work on time will react by shifting departure times in order to avoid
 470 congestion charging. It is very evident that individuals with different intentions respond very differently to
 471 the implementation of a toll ring. Similar results were found if segmenting on other latent variables.
 472
 473 Intention seems then to have an impact in prediction and such analysis would not be possible using the
 474 Scheduling Model alone. Although often only aggregate forecast are provided, information on how different
 475 segments of the population react to the same policy are particularly relevant in order to better target the
 476 policy intervention. The gain then from estimating a HCM and in particular for including the effect of
 477 intention stands primarily in a better understanding of the reasons “ about the cognitive process underlying
 478 the formation of preferences” (Paulsen et al., 2013) for departure time and their influence on aggregate
 479 market shares. Form psychological literature we know that intention can be changed with specific policies.
 480 The problem still remains how to apply the HCM to predict a change in individual intention.
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Figure 3: Substitution patterns after a change in the *transport system*.



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Figure 4: Substitution patterns after a change in the *activity system*.

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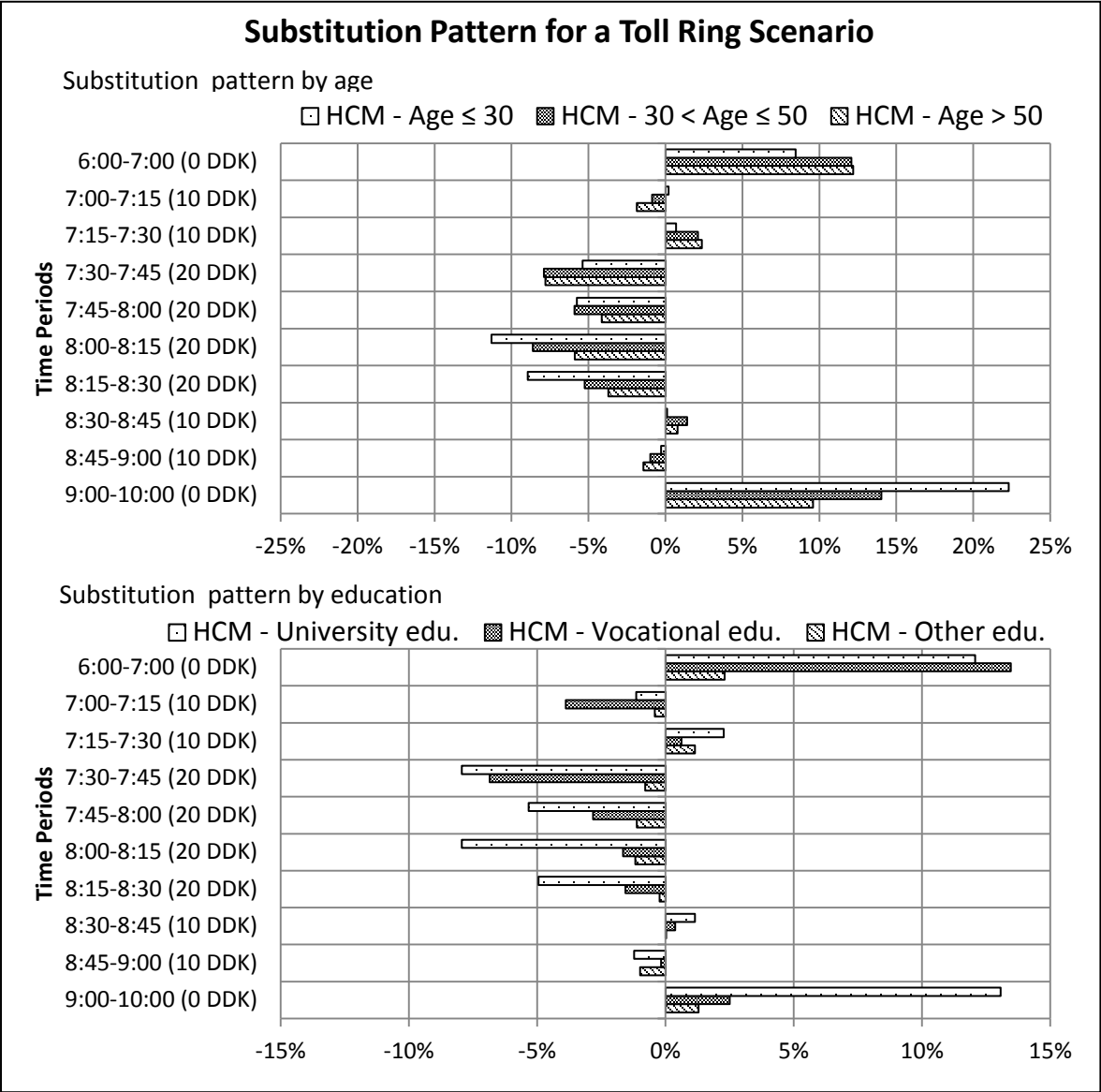


Figure 5: Change in the *transport system*.

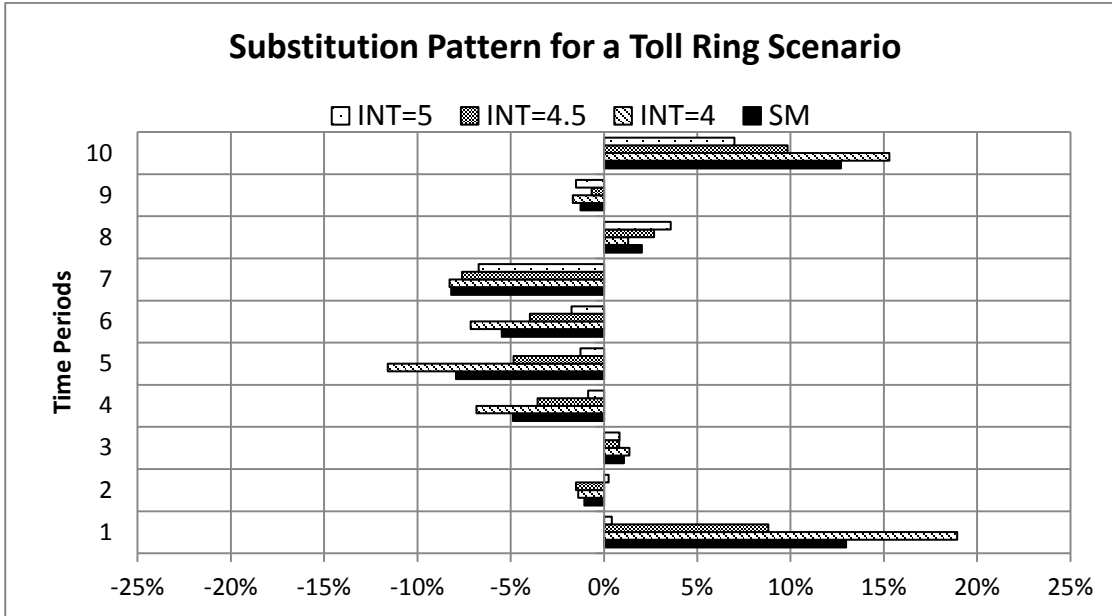


Figure 6: Change in the *transport system*: Substitution patterns by intention.

6 Discussion and Conclusion

In this paper we studied to which extent various psychological elements as defined in the extended Theory of Planned Behavior (TPB) affect individuals' decision on when to depart. In particular we focused on the role of intention as mediator between several latent effects and the current behavior. We allow for marginal utility of the scheduling attributes to depend on the individual intention to arrive on time at work. We found that both intention and attitude toward short travel time were statistically significant in explaining the choice, and attitude toward being on time, subjective norms and perceived behavioral control were highly significant in explaining the intention. Personal norms and perceived mobility necessities, were also tested, but found to be less important in terms of explaining departure time choices and to be non-significant in combination with the other latent variables.

We compared the hybrid choice model with a traditional scheduling model (SM), in some forecasting scenarios in which we modified both the *transportation system* and the *activity system*. As expected, we found that on an overall scale the SM and HCM had similar substitution patterns. However, the HCM allows forecasting in greater details among specific groups within the sample, which is not possible with the traditional SM. This effect is probably due to the fact that no socio-economic attributes were significant when included in the traditional SM. Intention seems then to have an impact in prediction and such analysis would not be possible using the Scheduling Model alone. The gain then from estimating a HCM and in particular for including the effect of intention stands primarily in a better understanding of the reasons "about the cognitive process underlying the formation of preferences" (Paulsen et al., 2013) for departure time and their influence on aggregate market shares. From psychological literature we know that intention can be changed with specific policies. The problem still remains how to apply the HCM to predict a change in individual intention.

Overall we believe the results presented in this paper to be an important contribution to the existing literature as it provides empirical evidence of the importance of accounting for unobservable psychological factors when dealing with departure time choices. We based our hybrid choice model on the TPB within a micro-economic framework. This is an interesting finding as it is not only statistically significant within a discrete choice framework, but also theoretically defensible as it is firmly grounded in the psychological literature which has acknowledge the importance of the Theory of Planned Behavior for years.

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