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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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Abstract

An increasing number of papers are focusing on integrating psychological aspects into the typical discrete choice models. The majority of these studies account for several latent effects, but they mainly focused on the direct effect of attitudes, perception, and norms in the discrete choice. None of them consider the effect of intention and its role as mediator between those psychological effects and the choice, as implied in the Theory of Planned Behavior. In this paper we contribute to the literature in this field by specifically studying the direct effect of the intention on the actual behavior, while attitude, social norms, and perceived behavioral control affect the intention to behave in a given way. We apply a hybrid choice model to study the departure time choice. For this, we used data from Danish commuters in the morning rush hours in the Greater Copenhagen Area. We found a significant effect of the intention to arrive at work on time on the departing time choice, and also a significant effect of the lower level mediators on the intention. Furthermore, the attitude toward short travel time was found to be significant. Finally, in terms of forecasting, we found that individuals who have a strong intention to be at work on time will be less likely to reschedule their departure time. This suggests that campaigns targeting the working culture could affect the subject norms among colleagues, which in turn influence individuals' intention to be on time or to reschedule to a less congested time slot.

Keywords: Hybrid Choice Model, Theory of Planned Behavior, Intention, Departure Time Choice, Scheduling Model

1 Introduction

During the past decade accounting for latent effects within discrete choices has gained increasing attention. The relevance for studying the link between internal (unmeasurable latent psychological construct) and external (measurable characteristics of alternatives and individuals) components of the decision process goes back to the seminal work of McFadden (2000) and Kahneman (2003). Several studies in the transport field[1] have incorporated psychological constructs to better explain the discrete choice and have used the hybrid choice model (HCM) framework (Ben-Akiva et al., 2002a; 2002b; 2012) to estimate the joint effect of these psychological latent effects 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; Raveau et al., 2010; 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 attitude and perceptions. For example Tudela et al. (2011), following the Theory of Reasoned Action, measured the effect of attitude, affective factors and habit in a mode choice context. 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. 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. (2013) 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 however accounts for the effect of intention to explain the effect of the latent construct in the actual behavior, as implied in the Theory of Planned Behavior (TPB).

The *Theory of Planned Behavior* (TPB), proposed by Ajzen (1991), is a generalization of the *Theory of Reasoned Action* (TRA, Fishbein and Ajzen, 1975), and is a widely recognized psychological theory in the context of travel behavior. The TPB assumes that *Intention* (to behave in a given way) is the direct predictor of behavior, while Intention (often also referred to as Behavioral Intention) in turn is influenced by a set of underlying constructs: *Attitude* (also often referred to as *Behavioral Attitude*), *Subjective (Personal and Social) Norm (SN)*, and *Perceived Behavioral Control (PBC)*. *Attitude* is the individual's belief to which degree the behavior makes a positive or negative contribution to that individual. *Subjective norm* relates to the perceived personal and social approval or disapproval towards a given behavior. Finally, *Perceived Behavioral Control* measures individuals' perceptions as to whether engaging in a behavior is hard or easy, and captures individuals perception towards whether they are capable and confident in engaging in the behavior. Thus, behavior which contributes to a positive attitude and is supported by significant peers, while at the same time individuals feels capable of overcoming that behavior is in turn also likely to form strong behavioral intentions towards that behavior.

As outlined above, the majority of the transportation literature which accounts for psychological aspects have mainly focussed on attitude. However, attitude has been shown often to be an inaccurate predictor of behaviour (Fishbein and Ajzen, 1975, Sheppard et al. 1988). On the other hand, previous studies in the psychological literature have found that intention is a better predictor of behaviour than attitude and perceptions (Ajzen, 1985, 1991, Fishbein and Ajzen, 1975, Gärling et al. 1998), which makes it particularly relevant. Fujii and Gärling (2003) states that: "The single most important insight from attitude theory is that behavioural intention is a better predictor of behaviour than any other measures". Thus in order to represent the underlying psychological decision process it was decided to account for intention, as implied in the

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.

Theory of Planned Behaviour. Furthermore, according to Bamberg (2012) the Theory of Planned Behaviour can be regarded “as a social psychological variant of the general rational choice approach”, and therefore seems like a good psychological theory to integrate with the classic utility theory.

Thorhauge et al. (2016b) 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. Their focus was to provide the theoretical background of the TPB in the departure time choice and discuss why it is essential to bring the TPB into the discrete choice of departure time. In their model, they used the sequential estimation, considering only the addictive effect of intention and did no study the impact 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.

The policy implication of accounting for latent psychological effects is still an open research question. There is a limited, but interesting discussion in the literature regarding the effect of latent variables in forecasts (Zhao, 2009; Yáñez et al., 2010; Paulssen et al., 2013; Chorus and Kroesen, 2014; Vij and Walker, 2015). In most of the cases the latent variables provide valuable information about the cognitive process underlying the formation of individual preferences for a given alternative that could prove useful to the design of policies but it does not improve the fit of the model, and does not have a strong impact in forecast. It is important to note that as reported by Vij and Walker (2015) “in terms of goodness of fit and consistency of parameter estimates, ICLV models offer no improvements over a reduced form choice model without latent variables. In terms of efficiency of parameter estimates, benefits will depend upon the underlying covariance structure of the data”:

The objective of this paper is to study the role of intention to behave in a given way into the actual observed behavior, where the intention is explained by the full latent constructs implied in the TPB. The contribution of the paper is twofold. First and foremost, it consists of accounting for the full TPB in the micro-economic framework (with a particular focus on intention) using a simultaneous hybrid choice model, which has never been done before. Secondly, it discusses and compares the impact of intention in prediction and how different segments of the population react to the same policy, which is particularly relevant in order to better target the policy intervention. The theoretical framework is applied to study the case of the departure time choice. In particular we extend the work of Thorhauge et al. (2016b) by (1) assuming that individual preferences for departure time is dependent on the latent construct, thus 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, i.e. how actual arrival time constraints at work impacts individuals perceived behavioral control, and (3) estimating the structural equation models of the latent variables simultaneous with the discrete choice model using an integrated choice and latent variable model and identifying the set of socio-economic characteristics that affect the departure time through latent constructs. In line with Thorhauge et al. (2016b) we focus on the intention to arrive at work on time.

The remaining part of the paper is structured as follows: Section 2 reports a discussion of the methodological background that motivates the model structure used in this paper. Then it describes the scheduling model and its extension to account for the latent effect of TPB. Section 3 describes the data collection, and Section 4 discusses the results of the model estimations. Section 5 reports the conclusions.

2 Model framework

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

The proposed model framework is illustrated in Figure 1. An extensive theoretical and empirical analysis has been conducted in order to define the psychological determinants of the departure time choice (a thorough discussion is reported in Thorhauge et al., 2016b). In line with Thorhauge et al. (2016b), we postulate that the discrete choice to depart early/late is directly affected by three main latent effects: the intention to arrive at work on time, the intention to have a short travel time, and the intention to have a low travel cost. In accordance with the Theory of Planned Behavior Intention is formed by the underlying subjective norm (SN), attitude toward being on time, and perceived behavioral control (PBC). In order to operationalize it, the latent constructs were simplified into a number of items believed to be the most important for the choice of departure time. More specifically, the Intention to be at work on time was believed to be the most important psychological construct of departure time choices, while the psychological dimension of travel time was measure through attitude only. The psychological component of cost is not explicitly considered in this study.

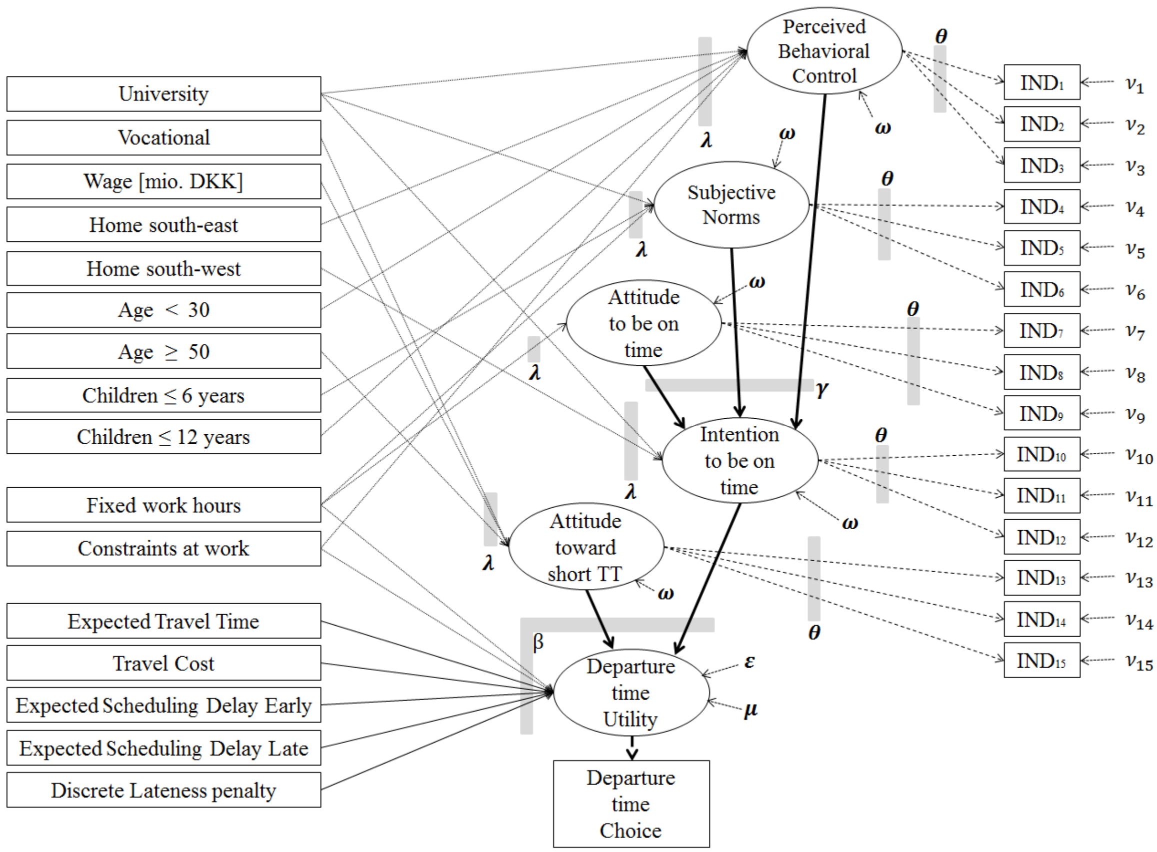

Figure 1 : Model structure of an integrated choice and latent variable model accounting for the extended Theory of Planned Behavior. Squared boxes represent observable components, while circles represent unobservable (latent) components. Dashed arrows represent measurement equations, while full arrows represent structural equations. Greek letters are parameters to be estimated.

Furthermore, 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 other than intention, also attitude toward short travel time and perceived mobility necessity 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 time, 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 set of sampled individuals, and $t = \{1, \dots, T\}$ a set of repeated observations from each 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:

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

Where

- $V(SM)_{jqt}$ is the systematic 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:

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

  with $i=\{1,\dots,I\}$ 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. they account for 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:

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

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

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

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

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

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 and in accordance with framework reported in Ben-Akiva et al. (2002b), the utility (U_{jqt}) that individual q assigns to the departure time alternative j in the observation t, in a hybrid choice framework can be written as:

$$U_{jqt} = ASC_j + \left(\boldsymbol{\beta}_j^{SM} + \boldsymbol{\beta}_j^{SM \cdot LV} \cdot \boldsymbol{LV}_q\right) \cdot \boldsymbol{LoS}(SM)_{jqt} + \boldsymbol{\beta}_j^{LV} \cdot \boldsymbol{LV}_q + \mu_{jq} + \varepsilon_{jqt} \quad (7)$$

Where

- ASC_j is the alternative specific constant for alternative j.

- $\boldsymbol{LoS}(SM)_{jqt} = \{E(\boldsymbol{TT}), E(\boldsymbol{SDE}), E(\boldsymbol{SDL}), \boldsymbol{TC}, \boldsymbol{DL}\}$ is a vector of level-of-service characteristics, as included in the systematic utility of the scheduling model.
- $\boldsymbol{LV}_q$ is a vector of M latent variables measuring the latent psychological effect of individual q.
- $\boldsymbol{\beta}_j^{SM}, \boldsymbol{\beta}_j^{SM\cdot LV}$ and $\boldsymbol{\beta}_j^{LV}$ 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. Extreme Value 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 as:

$$LV_{qm} = \alpha_m + \boldsymbol{\lambda}_{m,SE} \cdot \boldsymbol{SE}_q + \sum_{n \neq m} \gamma_n LV_{qn} + \omega_{qm} \qquad \forall m, n \in M \tag{8}$$

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*.
- $\boldsymbol{SE}_q$ is a vector of individual and family socio-economic characteristics and $\boldsymbol{\lambda}_{m,SE}$ 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:

$$IND_{qrm} = \tau_{rm} + \theta_{rm} \cdot LV_{qm} + \nu_{qrm} \qquad \forall m \in M, r \in R \tag{9}$$

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*.
- τ_{rm} is the constant in the measurement equations for indicator *r* of the latent variable *m*.
- ν_{qrm} is a normally distributed error term for latent variable *m* with zero mean and standard deviation σ_ν.

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:

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

$$f_{IND_{qrm}}(\omega) = \frac{1}{\sigma_{\nu_{rm}}} \Phi\left(\frac{IND_{qrm} - (\delta_{rm} + \theta_{rm} \cdot LV_{qm}(\omega))}{\sigma_{\nu_{rm}}}\right) \qquad \forall m \in M, r \in R \tag{11}$$

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_{qm} and μ_{jn}:

$$P_{jq} = \int_{\omega} \left(\int_{\mu} \prod_{t=1}^{T} P_{jqt}(\mu_{jq}, \omega_q) f(\mu) d\mu \right) \prod_{m=1}^{M} f_{LV_{qm}}(\omega) \prod_{r=1}^{R} f_{I_{NDrm}}(\omega_m)\ f(\omega) d\omega \tag{12}$$

The log-likelihood function is given by the logarithm of the product of the unconditional probability, where δ_{jq} is an index that equals one if j is the alternative chosen by individual q:

$$LL = \sum_{q} \sum_{j} \delta_{jq} ln(P_{jq}) \tag{13}$$

The model was estimated using the software package PythonBiogeme (Bierlaire, 2016).

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 during the 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 that were needed to filter the sample and 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). The questionnaire only asked for the trips/activities of the person interviewed.
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. A more in-depth description of the flexibility of individuals can be found in Thorhauge et al. (2016b).
4) **A stated preference experiment** where individuals were asked to choose among three alternative departure times. 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). Thorhauge et al (2014b) explains in details how the stated choice experiment was designed.
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. For more on the design of the latent constructs we also refer to Thorhauge et al. (2016a).
6) **Socio-demographic information** about the respondents and their families such as age, profession, presence of children and age, income and so on.

The data was collected by sending e-mails to respondents in the target sample with a link to the survey. Email addresses were obtained by contacting companies and organization, and at the homepage of the Universities. The sample was collected at different companies, organizations and universities selected based on the number of workers and their location in central Copenhagen. More than 10,000 invitations were distributed via e-mail. A total of 2,369 replies were obtained, of those 923 were fully completed. The data were cleaned based on the requirement that individuals: 1) were between 18-70 years old, 2) worked in the city center of Copenhagen 3) went to work by car, and 4) arrived at work between 6-10 a.m. After carefully cleaning the data, the final sample consists of 286 respondents, with an average age of 47.52±10.40 (mean ±

std.dev.) years and average income of 575.077±244.202 DKK. Moreover, on average each respondent perform 1.22 tours and 3.13 trips per day. On average, each tour consists of 2.55 trips. The average commuting distance to work is 21.2±12.92 km, while the average person spends 31.7±12.7 minutes commuting to work. Figure 2 show some key demographics of individuals in the final sample. The indicators of the latent constructs are presented in table 1. A factor analysis showed that the indicators group together as expected capturing the intended latent constructs, except that the three latent constructs *intention*, *personal norms* and *attitude towards being late* scores high on the same factor, indicating that these constructs capture the same variance. However, in order to be consistent with the Theory of Planned Behavior we maintain these as separate constructs.

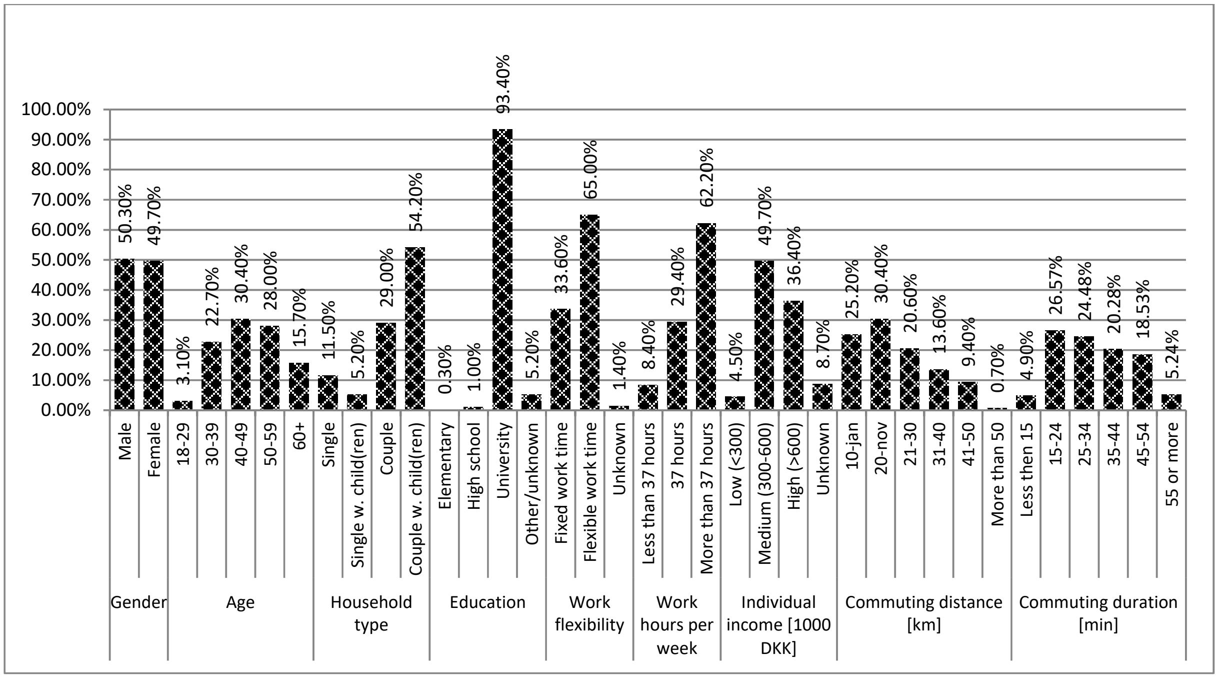

Figure 2: Socio-demographic characteristics of the sample (N=286).

Table 1: Overview of the indicators for the latent constructs. Bold numbers represent highest factor loadings for each item. * Order of Likert scale reversed.

Indicators	*M*	*SD*	Factor Analysis					
			F1	F2	F3	F4	F5	F6
Attitude towards being late, (Chrombach's α = 0.85)								
It is very important for me to be at work on time.	4.06	1.14	**0.85**	-0.05	-0.03	-0.04	-0.01	-0.07
Coming too late to work is very unpleasant for me.	3.73	1.29	**0.93**	-0.18	0.01	-0.15	0.01	0.00
It is problematic for me to be late for work.	3.63	1.35	**0.69**	0.01	-0.05	-0.17	0.00	-0.21
Subjective norm (Chrombach's α = 0.86)								
My colleagues think that I should be at work on time.	3.31	1.41	0.09	**0.80**	-0.03	-0.11	-0.02	-0.05
My boss thinks that I should be at work on time.	3.35	1.45	0.10	**0.78**	-0.07	0.00	-0.02	-0.07
People, who are important to me, think I should be at work on time.	3.27	1.35	0.06	**0.69**	0.06	-0.03	0.03	0.05
Perceived behavioral control (Chrombach's α = 0.65)								
It is easy for me to be at work on time.	4.18	0.96	0.02	0.01	-0.02	**0.63**	-0.07	-0.05
It is difficult for me to be at work on time.*	4.57	0.75	0.01	-0.01	0.05	**0.62**	0.14	0.03
It is possible for me to be at work on time if I want to.	4.22	1.08	0.00	0.16	0.10	**-0.59**	0.06	0.07
Intention (Chrombach's α = 0.81)								
I intend to be at work on time in the near future.	4.38	0.92	**0.62**	0.13	0.02	0.21	0.08	0.07
I intend to avoid delays in arrival time at work in the near future.	3.92	1.15	**0.54**	0.17	-0.02	-0.01	0.11	0.19
I plan to be at work on time in the near future.	4.31	0.97	**0.67**	0.09	0.03	0.22	-0.01	-0.05
Attitude towards short travel time (Chrombach's α = 0.67)								
It is very important for me to have short TT to/from work.	3.77	1.12	0.03	0.00	-0.01	0.07	**0.63**	-0.07
Having a long TT to/from work is very stressful for me.	3.53	1.22	0.02	-0.03	0.03	-0.14	**0.61**	0.01
I don't care about long TT to my work. *	4.35	0.95	0.06	-0.02	0.03	-0.05	**-0.60**	0.00
Perceived mobility necessities (Chrombach's α = 0.83)								
The organization of my everyday life requires a high level of mobility.	3.40	1.25	0.02	0.00	**0.80**	-0.03	0.05	-0.04
I have to be mobile all the time to meet my obligations.	3.16	1.29	-0.07	0.07	**0.84**	0.01	-0.07	0.00
My work requires a high level of mobility.	2.94	1.28	0.08	-0.12	**0.67**	-0.04	0.01	0.00
Personal norm (Chrombach's α = 0.85)								
I feel obliged to be at work on time.	4.09	1.16	**0.72**	0.17	0.04	0.05	-0.05	-0.02
Being late for work is against my principles.	4.24	0.96	**0.73**	0.03	0.07	0.15	-0.08	0.10
I feel very bad about being late for work.	3.86	1.19	**0.81**	0.00	-0.04	-0.05	-0.04	0.03
Attitude towards being flexible (Chrombach's α = 0.65)								
I am willing to depart earlier or later if it can reduce my travel time.	3.36	1.27	0.11	-0.05	-0.04	-0.06	0.00	**0.67**
I am willing to change my work time to avoid rush hours.	3.06	1.42	-0.09	0.01	-0.01	-0.03	-0.05	**0.62**

As detailed in Thorhauge et al. (2016b) our sample cannot claim to be representative according to a chi-square test against the Danish National Travel Survey, except for a few characteristics, such as gender distribution and more importantly commuting distance and duration to work. This is not surprising given that we specifically targeted certain companies, organizations and (especially) universities; our sample is in fact biased towards high-skilled labor forces, typically more flexible and slightly wealthier than the average population. Nonetheless, our results are still relevant because the high-skilled labor force is however an important segment of the population commuting to the central business district (CDB). More details on the survey questionnaire and data collection can be found in Thorhauge et al. (2016a).

4 Results

In this section we will discuss the results of the estimation of the hybrid choice model accounting for the extended Theory of Planned Behavior (TPB) in the scheduling model (SM). Table 2 reports the model results. The choice set in the discrete choice model consists of three departure time options (one similar to the reported trip, one earlier, and one later), while the dependent variable is the actual choice of departure time. Before estimating the Hybrid Choice Model (HCM) depicted in Figure 1, simple models with only one LV each were estimated to define the socio-economic characteristics that explain each latent construct. The socio-economic variables included in Table 2 are those that were highly significant when each LV was estimated alone and also when the full TPB was estimated without panel effect. For a fair comparison all the socio-economic characteristics included in the TPB were also tested directly in the SM, i.e. interacting with the attributes of the scheduling model or summed. However, none of them resulted in parameter estimates significantly different from zero, except from one parameter, which had an incorrect sign. This result is interesting as it reveals that the psychological construct is what indeed explains heterogeneity in preference in our context.

In the remaining part of this section, we will discuss the parameter estimates. We will discuss first the direct predictors of the choice, then the indirect predictors within the TPB, and finally the socio-demographic variables in the structural equations of the LVs.

Regarding the departure time choice we see in Table 2(a) that in both models (SM-alone and HCM) all coefficients are negative and are highly significant. We estimated various Hybrid Choice Models in order to test different ways of including the latent variables, i.e. additive and in interaction with level of services attributes. As described above our hypothesis was that the latent variables not only influenced the preference for a specific departure time, but also how individuals perceive a unit variation in the characteristics of the alternative. This was confirmed empirically in our data, as shown in table 2. Furthermore, the latent variables were not found to be significant when added to the utility functions. Instead, in the HCM the scheduling variables, i.e. expected scheduling delay early, expected scheduling delay late and the discrete lateness penalty (DL), interacts with the intention to be at work on time. In line with previous literature, all parameters for the level of service attributes are negative and significant ($p < .005$), with the exception of DL for individuals without arrival time constraint at work, which is however not significantly different from zero. This means that the penalty for rescheduling is not influencing individuals without constraints at work, whereas for individuals with constraints at work it increases with the intention to arrive at work on time. Furthermore, we found the attitude toward short travel time to be statistically significant when interacted with the expected travel time. The negative parameter is expected; as it means that a high attitude toward short travel time decreases the marginal utility for the expected travel time. Finally, we also attempted to interact perceived mobility necessity with the expected travel time, but that was not statistically significant, and it was not included in the final model.

Focusing on the lower level effects (i.e. the variables that affect intention) in Table 2(b), we found attitude toward being on time, subjective norms, and perceived behavioral control to be statistically significant as mediators for intention. The Likert scale of the indicators where flipped in order to go in the same direction for easier interpretation in the model. The indicators that were recoded are marked in Table 1. Thus, all parameters are positive, as expected, due to the direction of the indicator statements. More specifically, if the respondents had a high agreement with attitude toward being late, subjective norms, and perceived behavioral control, they were also more likely to have a high agreement with the intention to be at work on time. This is line with the findings in Thorhauge et al. (2016b).

We tested an extension of the TPB adding personal norms as a mediator for intention alongside attitude toward being on time, subjective norms, and perceived behavioral control. We found that when adding this latent variable to the TPB structure the other LVs become unstable. More specifically we found that attitude toward being on time and subjective norms decrease in magnitude (albeit they maintain the same sign). The findings suggest that we could estimate either personal norms or attitude toward being on time. This result was expected because in the factor analysis we found that personal norms could be grouped with attitude toward being on time and with intention. As the structure of TPB is already firmly grounded in the literature, we chose to disregard personal norms for further analysis at this point. Finally, as suggested by the TPB we also tested the influence of PBC directly on the choice, but found this relation to be insignificant.

Table 2(a): Model estimates of Scheduling Model, i.e. the discrete choice model.

Model	**Scheduling Model alone (M1)**		**Hybrid Choice Model (M2)**	
Work Hours	**Flexible**	**Fixed**	**Flexible**	**Fixed**
Travel cost – TC	-0.188 (-9.49)	-0.094 (-4.79)	-0.181 (-9.44)	-0.083 (-3.71)
Expected travel time – E(*TT*)	-0.239 (-9.05)	-0.128 (-4.57)		
E(*TT*) * *Attitude toward short travel time*			-0.060 (-8.88)	-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 (-6.97)	-0.027 (-7.52)
Discrete lateness penalty – DL	-0.003 (-0.01)	-0.666 (-3.15)		
DL * *Intention*			0.015 (0.29)	-0.153 (-3.00)
Generic parameters	**All individuals**		**All individuals**	
Expected scheduling delay early – E(*SDE*)	-0.040 (-4.90)			
E(*SDE*) * *Intention*			-0.009 (-5.00)	
ASC (Early Departure)	-1.260 (-3.06)		-1.200 (-3.03)	
ASC (Late Departure)	-0.517 (-1.41)		-0.483 (-1.30)	
St.dev (Early Departure)	-2.270 (-11.83)		2.260 (11.66)	
St.dev (Late Departure)	-2.580 (-12.55)		2.640 (10.00)	
Corr (Early-Late Departure)	-1.540 (-5.27)		1.760 (3.55)	
Model summary				
# draws	1000		1000	
Sample size:	2515		2515	
Final log-likelihood for the DCM:	-1753.947		-1752.383	
Final log-likelihood for the HCM:	-		-7467.455	
Rho-squared for the DCM	0.365		0.366	
AIC for the DCM	3536.062		3532.766	
BIC for the DCM	3617.514		3614.386	

Table 2(b): Model estimates of the latent variable part. Numbers in brackets represents t-test against zero.

Model		Hybrid Choice Model (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		3.560 (34.94)	1.170 (2.52)	3.740 (47.53)	3.790 (22.16)	4.610 (28.95)
Sigma		-0.370 (-3.04)	-0.790 (-4.16)	-0.089 (-1.65)	0.091 (1.00)	-0.486 (-4.18)
Constraints at work						-0.306 (-2.62)
Fixed Work Hours				0.891 (7.62)	1.100 (7.34)	
Education at university level			-0.210 (-2.42)		-0.748 (-4.16)	-0.269 (-1.82)
Vocational education		-0.301 (-1.79)				
Wage [mio. DDK]		8.720 (2.22)				
Home southeast of CPH						-0.231 (-1.45)
Home southwest of CPH			-0.159 (-1.45)			
Age $<$ 30						-0.528 (-1.57)
Presence of Children ≤ 6 years old					-0.404 (-2.35)	
Presence of Children ≤ 12 years old		0.256 (2.21)				-0.206 (-1.82)
LV: Attitude toward being on time			0.472 (6.44)			
LV: Subjective norms			0.178 (3.73)			
LV: Perceived behavioral control			0.224 (2.64)			
				Measurement equations		
Indicator 1:	St. dev	-0.154 (-1.76)	-0.655 (-5.13)	-0.548 (-4.61)	-0.421 (-1.79)	-0.343 (-3.00)
Indicator 2:	Intercept	-0.340 (-0.7)	-0.213 (-0.59)	-0.672 (-2.37)	0.065 (0.18)	0.064 (0.11)
	LV coeff.	1.030 (7.69)	0.944 (11.76)	1.090 (16.66)	0.993 (9.40)	0.993 (6.88)
	St. dev	-0.024 (-0.37)	-0.105 (-1.56)	-0.339 (-4.93)	-0.299 (-2.09)	-0.137 (-1.32)
Indicator 3:	Intercept	1.050 (1.77)	-0.631 (-1.93)	-0.464 (-1.51)	0.762 (2.69)	1.610 (2.53)
	LV coeff.	0.874 (5.54)	1.130 (16.27)	1.010 (13.89)	0.757 (9.01)	0.709 (4.76)
	St. dev	-0.342 (-3.00)	-0.768 (-5.16)	-0.089 (-1.21)	-0.045 (-0.63)	-0.523 (-4.48)

Turning our attention to the remaining socio-demographic variables in the structural equations of the latent variables, Table 2(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 with vocational education have lower attitude toward short travel time, 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.

The presence of children under respectively 6 and 12 years of age negatively influences 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 arrive at work on time. This is likely to be due to household obligations: so for example if individuals have escorting trips in the morning it is likely that they 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 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 respondents who have fixed work hours have higher subjective norms and attitude toward being on time at work. 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. 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 time 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 would 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 did not significantly influence the choice directly (not even when the LVs 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 and important 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 3 summarizes some characteristic of the intention and the attitude toward short travel time, as these are the two latent variables that directly affect the departure time utility. Figure 3 shows the marginal utility of the scheduling delays as a function of intention and attitude toward short travel time for both the Scheduling Model and the hybrid choice model. These are computed via simulation of the structural equations. More specifically, the standard scheduling model is not able to capture any variance in the preferences due to latent constructs (the lines are horizontal), but, 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 for 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 3: Descriptive statistics of the expected values for the latent variables in the sample..

Latent variable	Mean	Std. Dev	Min	Max
Intention to be on time	4.38	0.31	3.96	5.19
Constraints at work	*4.53*	*0.33*	*3.96*	*5.19*
No Constraints at work	*4.23*	*0.22*	*3.96*	*4.86*
Attitude toward short travel time	3.77	0.17	2.27	4.08
Fixed working hours	*3.76*	*0.15*	*3.33*	*4.02*
Flex working hours	*3.80*	*0.15*	*3.33*	*4.08*
Attitude toward being on time	4.04	0.42	3.74	4.63
Subjective norms	3.37	0.58	2.64	4.89
Perceived behavioral control	4.18	0.20	3.60	4.61

Following Yáñez et al. (2010) we tested two forecast scenarios. The first implies a change in the transport system, i.e. the impact of introducing a toll ring around Copenhagen (Figure 4). Similarly to Thorhauge et al. (2016a), we assumed a charge of 20 DKK (approximately 2.50 €) in the central peak period between 7:30-8:30, a charge of 10 DKK (approximately 1.25 €) 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. A price range of 10-20 DKK is in line with the toll ring systems implemented in other Scandinavian cities, such as Stockholm, Göteborg, and Oslo (Transportstyrelsen, 2015a; 2015b, Fjellinjen, 2015). In the second scenario we tested a change in the activity system, assuming that all commuters have flexible work hours (Figure 5). We are aware that such an assumption is unrealistic, but it is useful and interesting to study the performance of the HCM.

In the stated choice experiment respondents were presented with three alternative departure times: equal to current departure time described in the travel survey, earlier and later. For the forecast, it is desirable to present departure time (intervals) as absolute numbers, i.e. 7:30, 7:45, etc., in order to evaluate policy implications. Thus, 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. For each of the 10 time periods we relied on the Danish National Travel Survey for obtaining the level-of-service data, which cannot directly be transferred from the stated choice experiment. The alternative specific constants for the 10 departure time intervals were then calibrated based on the actual departure times observed for the respondents. More specifically, this was done by fixing the scheduling preferences obtained from the model estimation, while estimating the alternative specific constants based on the level-of-service from the Danish National Travel Survey. Furthermore, we also estimated the scale-parameter, to account for difference in scale across data samples.

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. Results in Figure 5 show that assuming all individuals to have flexible work hours and no constraints at work does not change the overall departure time substitution patterns much unless a toll ring is also introduced (the change in market shares is less than 5% for all departure time slots if a toll ring is not introduced). However, when a toll ring is also introduced, the respondents are given an incentive (i.e. avoiding the congestion charging) to reschedule their departure time, and the substitution among departure time slots therefore increases. We note that there is no much difference in the forecast using the HCM and the SM without socio-demographics. This makes sense because the scenario is evaluating a change in the transport system that is adequately captured by both model structures. This confirms some recent concerns about the benefit of using HCM in prediction (Yáñez et al., 2010; Chorus and Kroesen, 2014; Vij and Walker, 2015).

However, since the HCM allows capturing the effect of the socio-demographic variables, significant differences in forecasts are found if we look at the market shares for different groups in the sample. Figure 6 show that when a toll ring is introduced younger people (i.e. below 30) are more likely to reschedule, probably due to the fact that such individuals have fewer obligations. The elderly segment of the work force is instead less likely to reschedule, possibly because they tend to be more driven by habits. We also see that individuals with a university degree prefer to reschedule both earlier and later to avoid the congestion charging, possibly because these individuals are also more likely to be flexible, while individuals with vocational education only reschedule to an earlier departure time in order to avoid congestion charging. We note that in our case the inclusion of socio-demographic variables in the SM model was not found to be significant, their omission does not affect then the fairness of the comparison and indeed confirm the important of incorporating the latent effects.

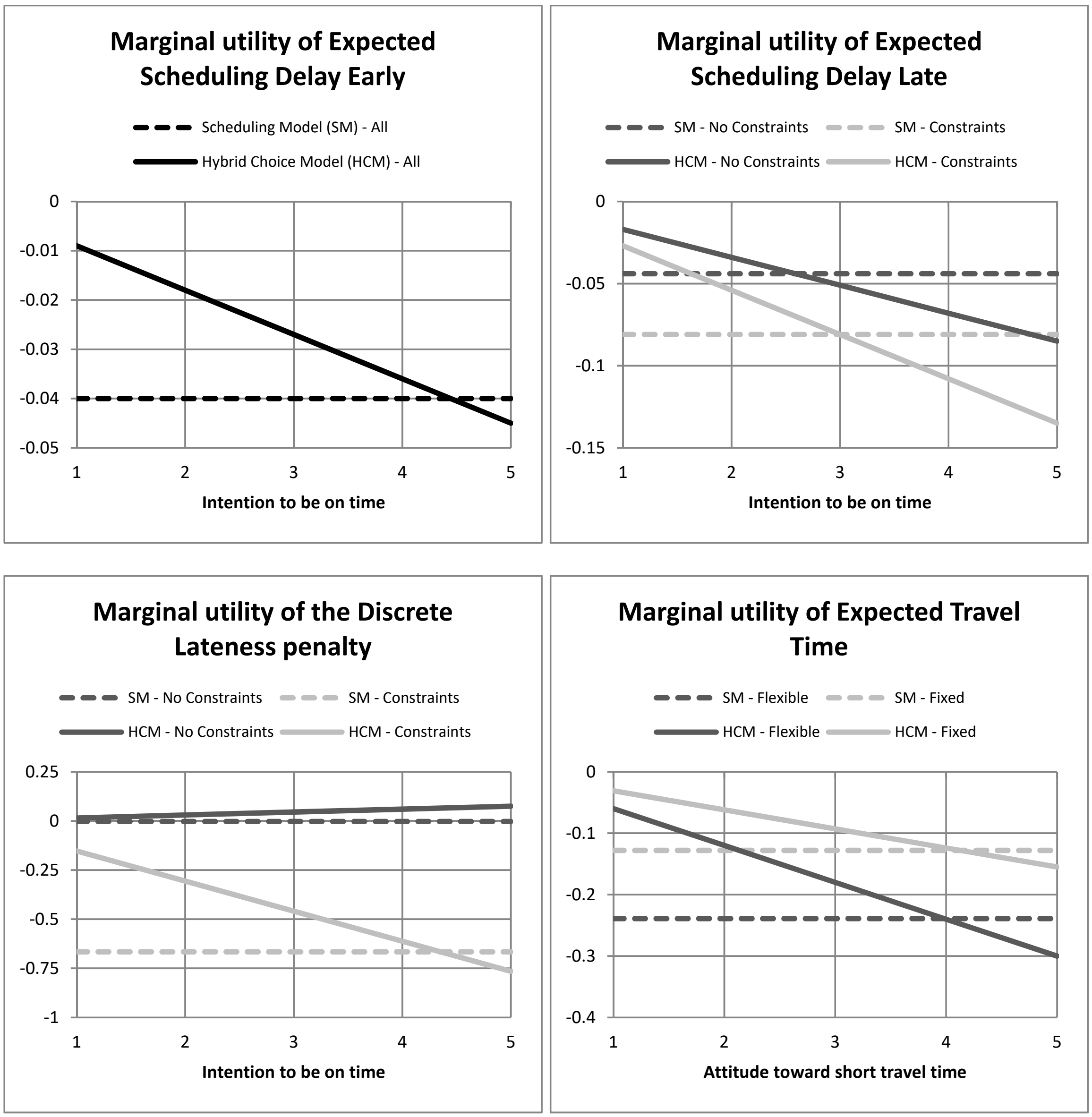

Figure 3: Marginal utility of the scheduling model attributes.

The major differences appeared between fixed and flexible individuals, and different segments in the sample, but both model structures (SM-alone and the HCM) predict similar changes. However, different substitution patterns are seen when segmenting on the level of intention to be at work on time. As seen in Table 3 all individuals agree on being at work on time (i.e. minimum level of intention is just below 4 on a 1 to 5 Likert scale), hence the segmentation is between individuals who *agree*s and those who *strongly agrees*. We divided the individuals into three segments based on the level of intention, thus defining intervals around 4, 4.5, and 5, and computed the substitution pattern for each segment (Figure 7). When a toll ring is introduced, individuals who have a strong intention to be at work on time will not reschedule to a later departure time options, while individuals with a lower intention to be at work on time will react by shifting departure times in order to avoid congestion charging. It is very evident that individuals with different intentions respond very differently to the implementation of a toll ring. Similar results were found if segmenting on other latent variables.

Intention seems then to have an impact in prediction and such analysis would not be possible using the scheduling model alone. Although often only aggregate forecast are provided, information on how different segments of the population react to the same policy is particularly relevant in order to better target the policy intervention.

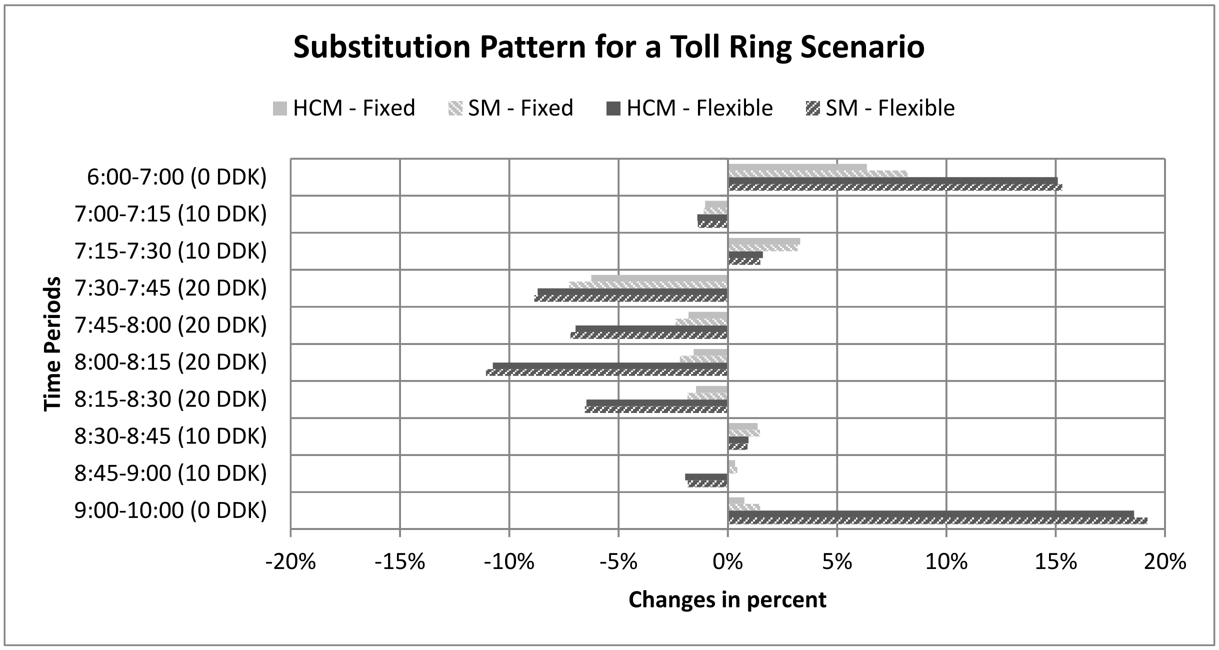

Figure 4: Substitution patterns after a change in the *transport system*.

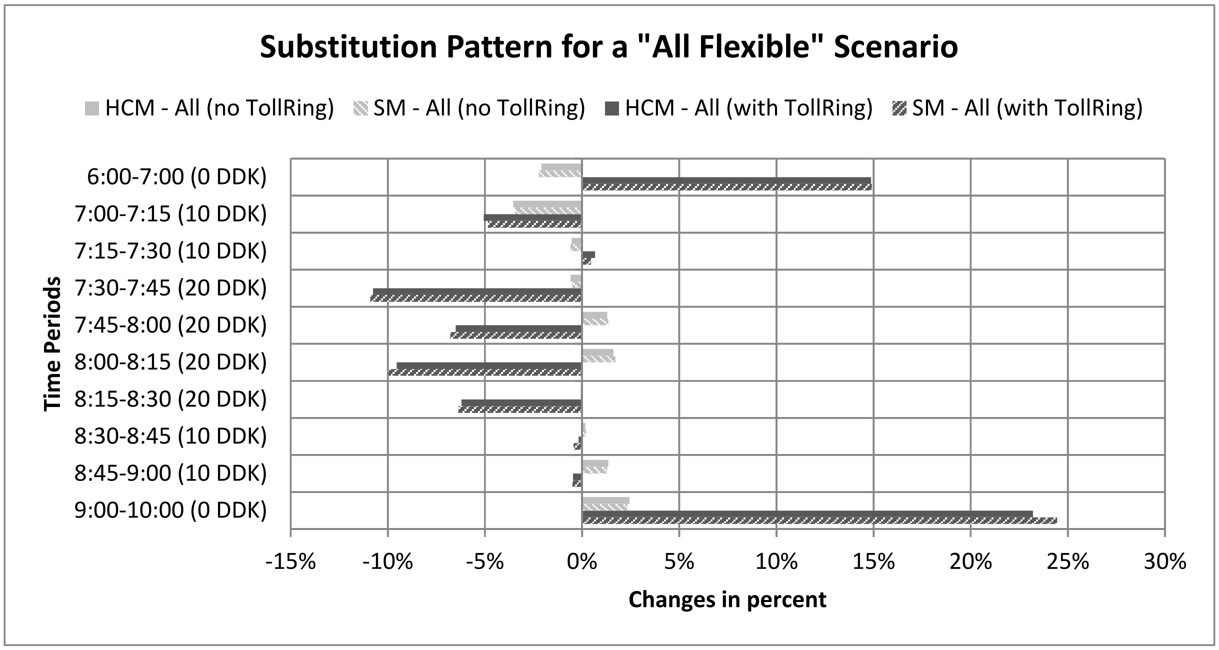

Figure 5: Substitution patterns after a change in the *activity system*.

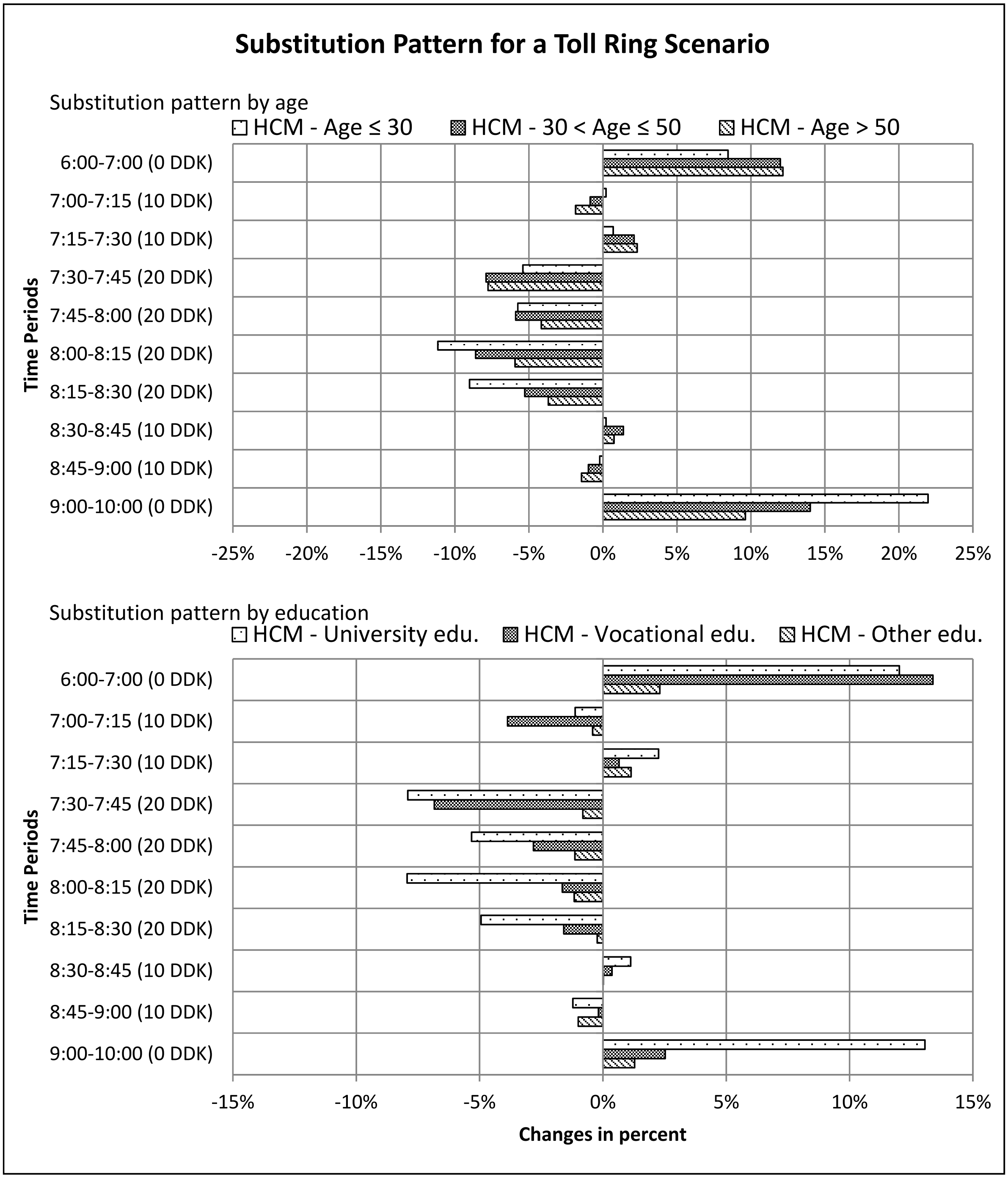

Figure 6: Change in the *transport system*.

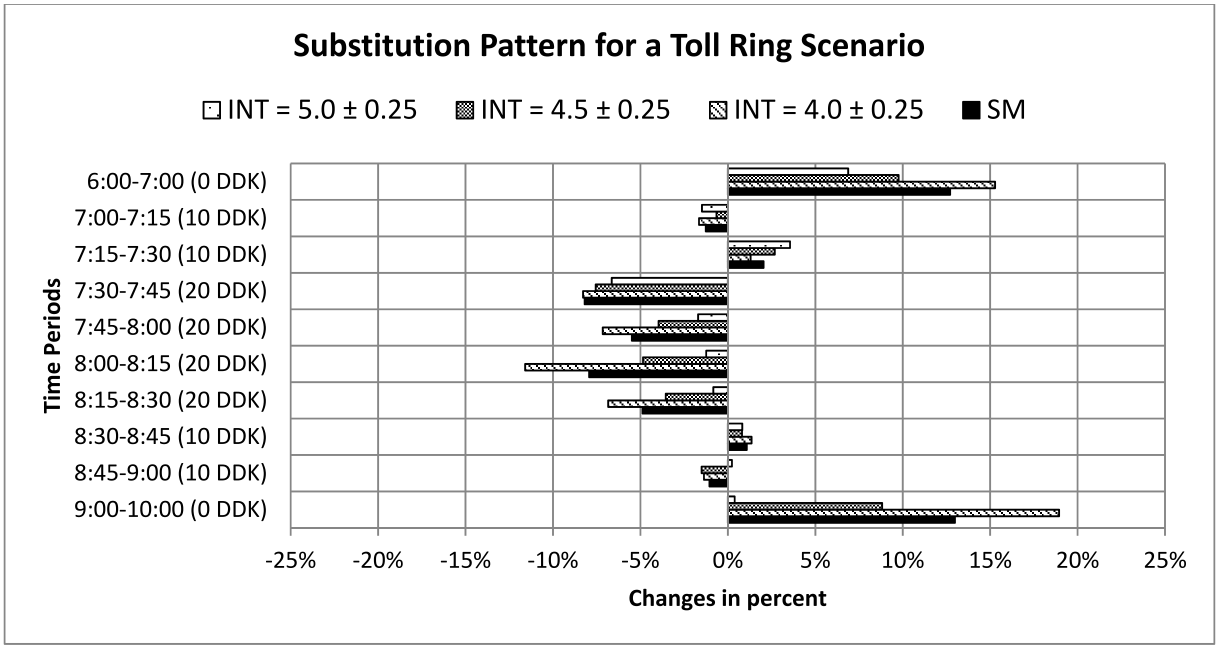

Figure 7: Change in the *transport system:* Substitution patterns by intention.

6 Discussion and Conclusion

In this paper we studied the role of intention as mediator between several latent effects and the current behavior and to which extent various psychological elements as defined in the extended Theory of Planned Behavior (TPB) affect individuals' decision on when to depart. We allowed for the marginal utility of the scheduling attributes to depend on the individual intention to arrive on time at work and found that the penalty for late (and early) arrival increases as intention towards arriving at work on time increases. 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 forecasting scenarios where 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. It is theoretically possible that this effect it is due only to the effect of the socio-economic characteristics and not to the psychological structures. If this is the case, a traditional SM that includes socio-economic characteristics will give the same results as the HCM. However, if the socio-economic attributes does not have any (significant) effect when included in the traditional SM, then it is clear that the psychological effects are playing an important role and the use of HCM is superior. Intention seems then to have an impact for 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" (Paulssen 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 intentions of individuals.

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 defendable as it is firmly grounded in the psychological literature which has acknowledge the importance of the Theory of Planned Behavior for years.

It is important to highlight that the sample used in this study cannot be considered representative for car commuters in general. In particular, people with flexible working hours are overrepresented. Identification of hybrid choice models require large samples and the relatively small sample size used in this study did not allow us to estimate an all-encompassing model. With the possibility to enlarge the dataset an important extension of this work consists for example in exploring the role of the objective and subjective constraints further as these plays a crucial role in departure time choice (Thorhauge et al., 2016a).

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Conflict of interest statement

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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