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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 start time or in terms of constraints in arrival time at work. Although used for the same purpose, these two questions can convey different types of information. Moreover, constraints in departure time are often related not only to the main work activity, but to all 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. We set up a survey to collect detailed data on the full 24-hour out-of-home activities and on the constraints for each of these activities. We then built a stated preference experiment to infer preferences on departure time choice, and estimated a mixed logit model, based on the scheduling model, to account for the effects of daily activity schedules and their constraints. Our results show that measuring flexibility in terms of work start time or constraints at work does not provide exactly the same information. Since one-third of the workers with flexible working hours in the survey indicated that they have restrictions on late work-arrival times, their willingness to pay will be overestimated (almost doubled) if flexibility information is asked only in terms of fixed/flexible working hours. This clearly leads to different conclusion in terms of demand sensitivity to reschedule to a later departure time. 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 towards a late departure time, is strongly overestimated (the predicted shift is more than double) when the effect of non-work activities and their constraints is not accounted for.

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,

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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; Bianchi et al., 1998; Hess et al., 2007a), and are even less likely to change their work and residential location (Goulias et al., 2013). 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. the 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 the) scheduling delay will equal zero. The SM was later extended to include travel cost (Small, 1987), a discrete lateness penalty to specifically capture the initial impact of late arrival (Noland and Small, 1995) and travel time (un)reliability (Small et al., 1995, 2000; Noland and Small, 1995; Noland et al., 1998; Small and Lam, 2001; Ettema et al., 2004b; Tseng et al., 2005, 2011; Börjesson, 2007, 2008, 2009; 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-variant model is theoretically equivalent to the scheduling model, but Börjesson et al. (2012) did not find them empirically equivalent.

Crucial in studying the departure time is whether individuals are flexible or not in their choices. 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 term for both scheduling delays, early (*SDE*) and late (*SDL*), indicating that the marginal disutility of being delayed decreases as the delays increase. Similar results were found in Polak and Jones (1994). Mannering (1989), who 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 Kristoffersson (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 min late with respect to their official work starting hours and found that highly flexible people value arriving late at work less, while Asensio and Matas (2008) used the same definition but with a threshold of 10 min.

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 around the main purpose (in this case 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, 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 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 activities. But they account for that by 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 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. non-work activities) on the departure time preferences for the work trip. As commonly 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) specifically modelled 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 for 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 for work. In this research we aim to fill this gap. The overall purpose of this research is to explore to which extent the choice of departure time, and thereby the revealed willingness to shift (WTS) departure time 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 believe WTS and WTP are affected by the way information is asked because WTS and WTP are affected by flexibility at work and the way information is asked affects the definition of flexibility at work. We also provide empirical evidence of the policy implication in terms of their impact in the shift of the predicted demand. The working hypotheses 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 individuals 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 as 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 schedules, 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 derived from that (see for example Lemp et al., 2012).

The paper is 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 results from the models estimated and a discussion of the policy implication. Section 6 summarises 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. We also focused on morning commuting trips to work by car towards the city centre. This 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 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). When collecting samples at destination it is common to select the venues for interviewing people strategically, without them 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 and 10:00, or did not have a travel time to work (by car) between 10 and 65 min. According to the Danish National Transport survey (Christiansen, 2012), less than 8% of the individuals travelling by car into Copenhagen in the peak morning hours have a trip shorter than 10 min and only 7% have a trip longer than 65 min. After 'cleaning' the data, the final sample available for the model estimation consisted of 286 respondents.

The sample was collected using a web-based questionnaire[1] 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 information (in departure time studies) 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) was 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. (2016).
(6) *Demographic information* about the respondent and his/her family. For all the household members the following socio-economic information was collected: age, gender, 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 facilities at the residence place, and number of cars in 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 compared to an orthogonal design (Rose and Bliemer, 2009). In

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

particular, the D-efficient measure aims at minimising the determinant of the asymptotic variance–covariance matrix. Whatever efficiency 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 with respect to the preferred arrival time instead of 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 occur 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 min (based on the distribution of trip lengths in the 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 realized during the day. The extent to which other activities affect departure time for 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-mentioned 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 that 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 however skewed towards high education, flexible working hours and high 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 the 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 work start time 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 also implies 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 also involves 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 found 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) during the work tour[2] and (2) the distribution of stops within the trip chain. The number of stops during a tour measures how efficiently individuals organise their trips; it is expected that the more complex the work tour, 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 will prefer an earlier departure in order to be able to fulfil 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 in a single trip chain, $H > 0$ means that activities are spread across different trip chains inside the work tour. We defined the trip chains as follows:

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

[2] A work tour is here defined as a tour that includes a working activity performed during the morning peak hours. Each work tour can have two trip chains, which are the sequence of activities/stops realized on the way to work and on the way from work.

Table 1
Trips to main work destination.

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 2
Sample distribution of tours. Totals are shown in bold.

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**	**75.00**	**84.03**	**75.54**
H-WB-H	43.71	41.94	46.88	44.44	42.45
H-WB-Ot-H	20.98	23.12	16.67	21.53	20.14
H-Ot-WB-H	5.59	5.38	6.25	6.25	5.04
H-Ot-WB-Ot-H	5.94	8.60	1.04	8.33	3.60
Other types	3.85	3.23	4.17	3.47	4.32
2 tours	**18.53**	**16.13**	**23.96**	**14.58**	**23.02**
H-WB-H + H-Ot-H	10.49	10.22	11.46	9.03	12.23
H-WB-Ot-H + H-Ot-H	2.45	1.61	4.17	1.39	3.60
H-Ot-WB-Ot-H + H-Ot-H	1.40	1.61	1.04	0.69	2.16
Others types	4.20	2.69	7.29	3.47	5.04
3 or more tours	**1.40**	**1.61**	**1.04**	**1.39**	**1.44**

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 in arriving later, while 16% of the workers with fixed working hours declared they have 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.

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[3] (the latter four are also referred to as *other* purposes, "Ot"). As expected the majority of the sample (80%) has only one home-based work tour 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.

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

3.2. Flexibility on daily activities other than work

In this section we analyse the daily activities realized 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 analysis by trip chain. Table 4 reveals a clear pattern

[3] Although education is not a relevant category in our sample (as there are only three observations), we included it for completeness and consistency with the Danish National Transport Survey.

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

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, *before work*)	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, *after work*)	27.64	23.91	36.67	22.45	32.67

Table 4
Average numbers of activities/trips and distribution by purposes. Totals are shown in bold.

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
Others types	0.64	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
Others types	1.40	0	55	15	30
3 or more tours	**2.25**	**0**	**33**	**11**	**56**

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

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

of activities where individuals who perform only one main work tour a day, mainly have escorting activities. On the other hand, errands and leisure activities are mainly performed during 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 realized 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.

The average number of stops for other purposes (escorting, errands, leisure or education) in complex work tours (i.e. with at least 1 stop for other purposes during 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 value 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 work tour. 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 individuals with constraints (0.098).

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/without constraints on how late they can arrive at work. As expected, escorting trips are the most constrained ones in almost all the dimensions (temporal, spatial and social), while errands and leisure activities are the most flexible ones.

Table 6
Comparison between flexibility in work start time and restrictions in the departure time.

	Escort				Errands		Leisure			
	Home-Work (HW)		Work-Home (WH)		Work-Home (WH)		Work-Home (WH)		After Work (AW)	
Work start time	Fixed (%)	Flexible (%)	Fixed (%)	Flexible (%)	Fixed (%)	Flexible (%)	Fixed (%)	Flexible (%)	Fixed (%)	Flexible (%)
Temporal constraints										
Arrive later	80	68	91	72	31	18	0	33	67	59
Departure earlier	60	35	91	58	77	35	25	11	67	53
Other day	90	94	91	86	23	44	0	33	33	71
Other time	100	91	82	72	46	32	25	33	67	82
Spatial constraints										
Other place	100	100	100	97	46	21	0	22	83	88
Social constraints										
Other person	50	47	73	39	31	53	0	44	83	76
Decide yourself	70	53	73	58	77	35	0	11	33	53
Exclude activity	90	94	91	97	31	68	50	56	50	76
	Escort				Errands		Leisure			
	Home-Work (HW)		Work-Home (WH)		Work-Home (WH)		Work-Home (WH)		After Work (AW)	
Constraints on arriving late at work	Yes (%)	No (%)	Yes (%)	No (%)	Yes (%)	No (%)	Yes (%)	No (%)	Yes (%)	No (%)
Temporal constraints										
Arrive later	72	69	89	68	39	4	22	25	70	54
Departure earlier	56	31	74	61	78	17	22	0	40	69
Other day	89	96	89	86	35	42	11	50	70	54
Other time	89	96	84	68	39	33	33	25	80	77
Spatial constraints										
Other place	100	100	100	96	43	13	11	25	100	77
Social constraints										
Other person	50	46	47	46	43	50	11	75	60	92
Decide yourself	61	54	58	64	52	63	56	50	70	69
Exclude activity	94	92	95	96	52	63	56	50	70	69

Interestingly leisure activities are less constrained when realized within the main work tour than when they are realized 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 fewer 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 show 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 realized 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:

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

where U_{jnt} is the utility for individual n associated to alternative j, in choice task t, and ASC_j is the alternative specific constant for alternative j. $E(TT)$ is the expected travel time that accounts for the travel time variability. $E(SDE)$ and $E(SDL)$ are the expected scheduling delays for early and late arrival, respectively. TC is the travel cost and DL is the late penalty dummy variable. DL captures the initial penalty for late arrival, while $E(SDL)$ is a lateness penalty function based on the amount of late arrival. SE is a vector of individual socio-economic characteristics, while FC is a vector of variables that account for the effect of daily activities (trip complexity and activity pattern complexity) and flexibility constraints (through dummy variables) as defined in Section 3. Finally ε_{jnt} is a typical extreme value type 1 random term 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 alternatives. 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:

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

Analogously $E(SDE)$ and $E(SDL)$ are defined as:

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

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

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). Similarly, 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 Level-of-Service (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:

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

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

$$P_{n\mathbf{j}} = \int_{\mu} \prod_{t} P_{nj_t}^{MNL}(\mu) d\mu \tag{6}$$

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 Fetiarison, 2009). We first estimated simple ML models with only the Level-of-Service 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 for work. We discuss first the estimation results and then some policy implication in terms of their impact on 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 work start time (M1) and another model that accounts for the effect of having or not having constraints at work (M2). Table 7 reports the models estimated and the trade-offs (point values and interval 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) do 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 reflects the fact that flexibility is associated with less sensitivity to rescheduling. The ratios $E(SDE)/E(TT)$ and $E(SDL)/E(TT)$ in our sample are lower than what was 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 €/h on average for saving one minute of travel time, while fixed individuals are willing to pay approximately 12 €/h 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 €/h.

Following 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 the scheduling delay for both 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 working start times and restriction at work (or flexible working start times and no restriction at work), the results in Table 7 suggest that the way information about 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 the 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 the 0.10 level of significance). At the same time the results also suggest 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 for 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; Kristoffersson, 2013) the *E*(*SDE*) does not seem to be significantly different between fixed and flexible respondents, which confirms our findings. Disregarding this effect leads to overestimating the WTP for reducing *SDE* for individuals with unadjustable work time and underestimating the WTP for reducing *SDE* for individuals 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, i.e. based on the results found in M1 and M2, we defined a specification where for each attribute we used the flexibility measurement that worked better). 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 realizing 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 the 0.01 level of significance). Results show that for individuals with constraints at work, the more complex the main work tour (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. e*ntropy*). They are more likely to reschedule, and if they have *other* activities in more than one trip chain in the main work tour, 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 realized in tours not related to work (namely home-based tours realized after returning home from work) where it is clear that the penalty to reschedule

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

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)	−1.15	−1.8	−1.57	−3.16	−1.08	−1.9	−1.54	−2.84
ASC (late departure)	−0.948	−1.64	−0.875	−1.89	−0.62	−1.18	−1.02	−2.11
E(*TT*)	−0.137	−3.63	−0.238	−8.13	−0.159	−4.67	−0.246	−7.89
TC	−0.09	−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	−0.035	−3.36
E(*SDL*)	−0.115	−5.46	−0.085	−8.44	−0.129	−8.3	−0.073	−6.4
DL	−0.632	−2.54	−0.076	−0.42	−0.654	−3.21	0.25	1.17
	Generic for the entire sample				Generic for the entire sample			
St.dev (early departure)	−2.38	−10.16			−1.2	−3.46		
St.dev (late departure)	2.38	12.71			2.47	12.72		
Corr (early–late departure)	0.309	0.26			2.1	9.99		
Number of draws	1000				1000			
Number of observations	2515				2515			
LL(max)	−1790.37				−1779.61			
Rho2 (C)	0.33				0.34			
WTP [€/h] – Trade-offs	M1				M2			
	Fixed hours		Flexible hours		Constraints		No constraints	
E(*SDE*)/*TC*	4.641		1.802		4.52		1.44	
95% Interval confidence	(1.906–11.646)		(0.869–3.072)		(2.236–9.217)		(0.547–2.654)	
E(*SDL*)/*TC*	10.319		3.724		9.973		3.008	
95% Interval confidence	(5.365–23.035)		(2.598–5.316)		(6.265–17.912)		(1.906–4.56)	
E(*TT*)/*TC*	12.298		10.399		12.298		10.198	
95% Interval confidence	(6.909–20.646)		(8.542–12.579)		(8.188–18.169)		(8.316–12.426)	
E(*SDE*)/*E*(*TT*)	3.032		1.399		2.952		1.134	
95% Interval confidence	(1.408–7.15)		(0.724–2.228)		(1.625–5.525)		(0.466–1.954)	
E(*SDL*)/*E*(*TT*)	6.748		2.879		6.523		2.373	
95% Interval confidence	(3.402–16.488)		(1.987–4.19)		(4.038–12.088)		(1.488–3.66)	

the departure time is due to leisure activities spatially or socially constrained realized in the tour after the return from work. An activity realized 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 spatial 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.

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 increase the penalty for arriving late. However, we found that in our data the effect is more due 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 increases the penalty. At the same time any another activity that is constrained increases the penalty for 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 min each were defined, except for the first and last intervals that were of 1 h 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 and 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).

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

Estimates	M3				M4			
	Value	Robust *t*-test	Value	Robust *t*-test	Value	Robust *t*-test	Value	Robust *t*-test
	Fixed hours		Flexible hours		Constraints		No constraints	
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	−0.18	−9.36
	Constraints		No constraints		Constraints		No constraints	
E(*SDL*)	−0.132	−9.44	−0.069	−6.57	−0.13	−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 work tour								
E(*SDE*) × Number of *Other* activities					−0.028	−2.98		
E(*SDE*) × Entropy of *Other* activities							0.065	2.42
Activities in trip chain HW								
E(*SDL*) × *Escort* activities with Temporal Constraints					−0.091	−1.65		
Activities in trip chain WH (dummy)								
E(*SDL*) × *Errands* activities							−0.055	−2.68
Activities in trip chain AW (dummy)								
E(*SDL*) × *Leisure* activities with Spatial Constraints							−0.149	−5.77
E(*SDE*) × *Leisure* activities with Social Constraints							−0.15	−7.82
	Generic for the entire sample				Generic for the entire sample			
ASC (early departure)	−1.13	−2.44			−1.12	−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 departure)	1.98	4.72			1.73	2.28		
St.dev (late departure)	−2.4	−13.04			−2.45	−12.76		
Corr (early–late departure)	−1.44	−2.71			−1.79	−2.03		
Number of draws	1000				1000			
Number of observations	2515				2515			
LL(max)	−1779.2				−1756.57			
Rho2 (C)	0.351				0.356			
WTP [€/h] – Trade-offs	M3				M4			
	Fixed		Flexible		Fixed		Flexible	
E(*SDE*)/*TC* (*all sample*)	4.55		2.19		5.09		2.23	
E(*SDL*)/*TC* (*all sample*)	11.37		3.95		11.35		4.21	
	Constraints		No constraints		Constraints		No constraints	
E(*SDE*)/*TC* (*all sample*)	3.58		2.42		4.31		2.13	
No activities other than work					3.89		2.33	
Leisure activities with Social Constraints in trip chain AW							8.92	
E(*SDL*)/*TC* (*all sample*)	9.71		3.46		9.66		3.83	
No activities other than work					9.89		2.96	
Escort activities with Temporal Constraints in trip chain HW					8.82			
Errands activities in trip chain WH					0		5.13	
Leisure activities with Spatial Constraints in trip chain AW					0		10.73	

Fig. 1 shows the policy implication of the two different ways of measuring flexibility at work. Results clearly show that indeed the prediction is different depending on how the information about flexibility 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.

Fig. 2 shows the effect on the shift in departure time predicted if we neglect the effect of other activities realized during the day and their constraints. Results clearly show that the shift in the departure time, especially towards 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

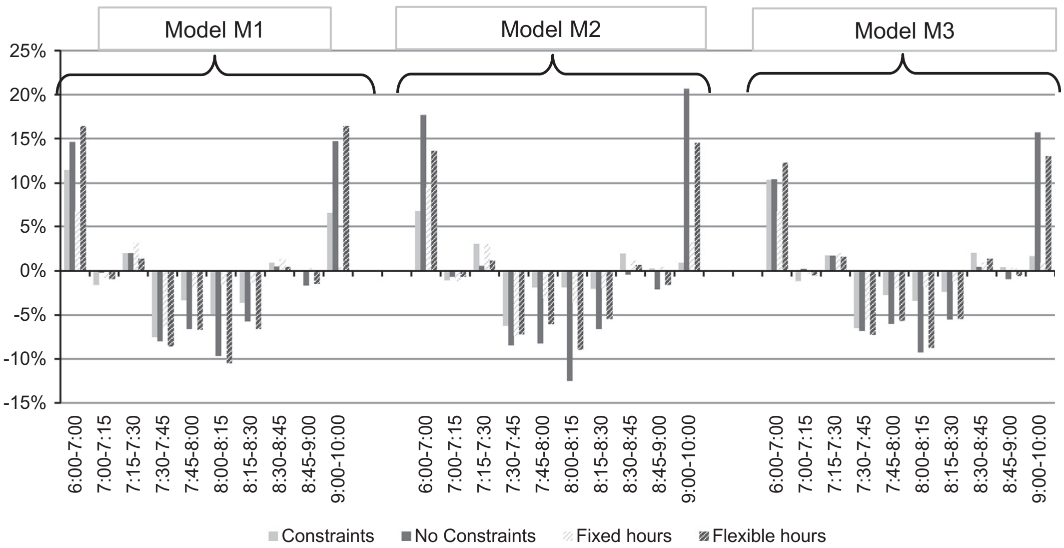

Fig. 1. Shift in departure time predicted after the application of the policy: effect of different ways of measuring flexibility at work.

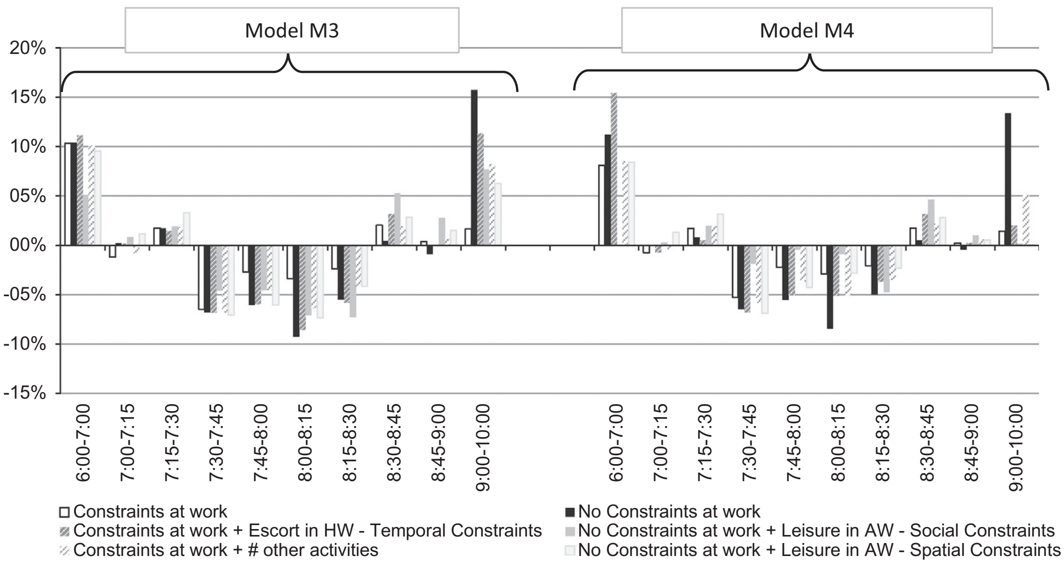

Fig. 2. Shift in departure time predicted after the application of the policy: effect of accounting for daily activity schedules and constraints.

neglects the effect of *other* activities and constraints strongly overestimates the willingness to shift, especially towards 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.

6. Conclusion

In this paper we investigated the choice of departure time for car commuting trips in the morning. We carried out this analysis by creating an efficient stated preference (SP) design in which individuals are given three options where price and time attributes are varied. The analysis, however, goes one step further and looks particularly at how flexibility or inflexibility of the main activity (in this case work) as well as other activities during the day, influence the departure time choice of commuting trips from home to work. Accounting for these flexibility constraints is important because these will generally influence individuals' decision 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 the willingness to pay (WTP) to avoid rescheduling the departure time, especially for individuals with adjustable work times.
– Constraints on other activities would cause the WTP for rescheduling early or late to increase as it represents 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 rescheduling to a later timeslot is only statistically different between individuals with and without constraints on 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 work start times in the survey indicated that they have restrictions on late work-arrival times, their willingness to pay will be overestimated (almost doubled) if flexibility information is asked only in terms of fixed/flexible work start times. 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 the 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 better explore 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 are relevant in the distribution of departure time and have a strong policy implication. Overall, neglecting the effect of daily activities other than work and their constraints strongly overestimates the willingness to shift towards 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 on leisure activities carried out in the evening after returning home from work are willing to pay 11 euros/hour on average for reducing *SDL*, which is almost three times the WTP of individuals without constraints at work *but* without other activities (3.80 euros/h) and almost approximately the same WTP of individuals with constraints at work (9.70 euros/h). This of course has relevant policy implications, and to validate these we assumed a forecasting scenario which introduces a toll ring around Copenhagen with prices ranging from 20 DKK in the most congested periods (7:30–8:30) to being free of charge outside the rush hours (before 7:00 and after 9:00). We found that, if the effect of daily activities other than work and their constraints is not accounted for, the predicted shift in departure time is almost three 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 chains in categories. A larger sample is probably needed for that. However, our findings clearly suggest that studies on departure time should account for the entire 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 non-work activities and their constraints on the departure time for work. A more comprehensive investigation should include all travellers who can decide to shift their travel times or activity schedules and durations, as well as the effect of travel time uncertainty. Some recent works on the scheduling problem have in fact showed that when travel time uncertainty increases commuters will shift from auto to public transport and the duration of the peak period on highway shrinks (Tian and Huang, 2015). Furthermore, if the time interval for which people can act in a flexible manner increases, the "peak shoulders" will be reduced, suggesting that flexible working hours are indeed a good countermeasure on the demand management side to cope with peak period congestion (Xiao et al., 2014).

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