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Mobility needs, activity patterns and activity flexibility: How subjective and objective constraints influence mode choice

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Abstract

Denmark is one of the world-leading countries in terms of bicycle infrastructure and has a relatively good public transport system. Yet, a large share of commuters in the Greater Copenhagen Area still uses the car on a regular or semi-regular basis, causing severe problems of congestion and pollution. This article seeks to understand to what extent individuals' perceived mobility necessities (PMN), activity pattern complexity, and temporal, spatial, social, or compulsory constraints in everyday activities inhibit switching from private motorized transport modes to more environmentally friendly modes. We formulate an Integrated Choice and Latent Variable model that accounts for PMN and activity patterns, complexity and constraints. To estimate the model, we used two datasets: the first dataset is the Danish National Transport Survey, which is a large dataset consisting of approximately 150,000 respondents; the second is a small(er) but highly detailed dataset, which contains relevant information regarding activity patterns, constraints and PMN. We found that the more complex the activity patterns are, the higher are both PMN and the probability of selecting car and bike, and this effect is even more evident when individuals are constrained by some activities. Consistently, individuals who perceive high mobility needs are more likely to select car and bike. The result that mobility needs and related constraints increase cycling conflicts with results found in low-cycling countries. Yet, it indicates that the bike can play a similar role as the car when the respective infrastructure is provided. Our results also indicate that structural improvements, such as flexible work and day-care times, day-care service close to the workplace, or escorting services for children are likely to lead to a substantial reduction in the use of the car.

42 **Highlights**

- 43 - Detailed information on perceived mobility needs as well as activity constraints (temporal, spatial,
44 social, and compulsory) were collected
- 45 - Perceived Mobility Necessities (PMN) are positively associated with car and bike use
- 46 - Individuals with complex activity patterns and activity constraints are less likely to select public
47 transport, and more likely to use car and bike
- 48 - PMN increase with the number of daily activities and constraints
- 49 - Commuters with high PMN are less likely to shift away from car to public transport as a result of a
50 policy that involve the implementation of designated bus lanes
- 51 -

52 **Keywords:** Mode Choice, Perceived Mobility Necessities, Daily activity patterns, Flexibility constraints,
53 Integrated Choice and Latent Variable Model

54

1 Introduction

Denmark – and Copenhagen in particular – is one of the world leading places in terms of bicycle infrastructure and demand (Haustein et al., 2019a; Pucher and Buehler, 2012). Yet, a large share of commuters in the Greater Copenhagen Area still uses the car on a regular or semi-regular basis (Vejdirektoratet, 2016), causing severe problems of congestion and pollution. It has been estimated that approximately 130,000 hours are wasted being stuck in traffic every day in the Greater Copenhagen Area, which equals 800-1100 million Euros per year (COWI, 2012; Municipalities, 2008). These effects are even more evident in other cities around the world, where the numbers of inhabitants and commuters are much higher than in Copenhagen, while bicycling is less common (or even non-existing) leading to even more severe transport problems.

In the last decades, city planners have looked at a variety of solutions to address this problem. Attempts have been made through improvements of alternative transport modes, such as public transport systems (e.g., the BRT-system “TransMilenio” in Bogota, Hidalgo et al., 2013) and bicycle infrastructure (e.g., Skov-Petersen et al., 2017). In addition, car-restrictive policies, such as road pricing (e.g., Börjesson et al., 2012) or parking management (e.g., Buehler et al., 2017) have been introduced in several cities. Besides these *hard* measures, *soft* measures, such as information provision and awareness campaigns have been used to achieve voluntary changes in mode choice (e.g., Bamberg, 2013; Cairns et al., 2008; Cherchi et al., 2017; Möser and Bamberg, 2008).

Despite this wide range of initiatives, cities around the world are still struggling with severe congestion problems (e.g., Becker et al., 2019) as many commuters are reluctant or unable to switch to alternative transport modes. Studies have shown that mode choice is one of the most in-elastic day-to-day travel decisions individuals make (Hendrickson and Planke, 1984; Hess et al., 2007). This makes it even more important and interesting to understand why individuals choose as they do in order to find the right leverage to promote a mode choice switch. While mode choice has been explained by a variety of factors and models, this paper focusses specifically on the effect of activity complexity and constraints from both the objective and subjective perspective.

1.1 Travel mode choice and the role of activities and constraints

The literature on factors influencing travel mode choice is vast (see a summary in Ortúzar and Willumsen, 2011). Of particular interest for this paper is research that has focused on activity participation and trip complexity and on subjective constraints and mobility needs.

Activity participation is an integral part of everyday life. Activities can be mandatory or discretionary (Yamamoto and Kitamura, 1999), performed alone or jointly with family and/or friends (Chandrasekharan and Goulias, 1999; Thorhauge et al., 2012; Yarlagaadda and Srinivasan, 2008), and restricted or non-restricted in terms of time and space (Bowman and Ben-Akiva, 2000).

Furthermore, to increase scheduling efficiency, trip chaining is becoming more important and has gained more focus from researchers (Cirillo and Axhausen, 2002; McGuckin et al., 2005). Several studies have investigated mode choice decision seeking to understand how to promote and increase ridership of environmentally friendly modes instead of the car (e.g., Chakrabarti, 2017), and many studies focus on how trip chaining influence the choice of transport mode, in particular bicycle (Cao et al., 2008) and public transport (Vande Walle and Steenberghen, 2006). Xianyu (2013) studied “whether the behaviour of linking activities to the work trip is conditional on the commute mode choice or vice versa”, and found the impact of activities on the mode choice to be the dominant relationship. Trip chaining is more likely to be undertaken using transport modes that are

98 spatially and temporally flexible, easy to access, and multi-objective travel friendly (Wan and Candidate,
99 2011), which seems most likely to be private modes, while public transport seems less suitable (Dong et al.,
100 2006). Ye et al. (2007) explored the relationship between commuters' mode choice and the complexity of their
101 trip chains and found that driving was associated with (more) complex commute chains. However, some
102 studies also find the reverse effect (Currie and Delbosc, 2011). Cherchi and Cirillo (2014) found that the type
103 of activities had little influence on the mode choice over a six week period, instead the preferences for a specific
104 mode was influenced by the amount of time allocated to activities. Furthermore, it has been found that morning
105 and evening commute stops (i.e. intermediate activities) are more likely to be carried out by women, and the
106 likelihood increases with age and income (Chu, 2003).

107
108 Subjective factors have often been operationalised in the theoretical framework of the Theory of Planned
109 Behaviour (TPB, Ajzen, 1991; see e.g. Bamberg et al., 2007; Donald et al., 2014; Lanzini and Khan, 2017).
110 Here, it has been shown that people's mode choice can be modelled by the intention to use a specific mode,
111 while intention itself is determined by three factors: (1) the degree to which the use of the respective mode is
112 positively or negatively valued (attitude), (2) the perceived social pressure to use the mode (subjective norm),
113 and (3) the perceived ability to use it (perceived behavioural control). Perceived behavioural control (PBC)
114 influences behaviour also directly. The higher the perceived restrictions, the less relevant is the intention and
115 its antecedents.

116
117 Haustein and Hunecke (2007) extended the TPB by introducing the construct of perceived mobility necessities
118 (PMN). Background for this addition was that the operationalisation of PBC mainly focuses on transport-
119 related constraints (e.g., trip distance, car/bike availability, transport infrastructure, see Bamberg, 2012), while
120 constraints related to the personal living situation are only captured indirectly. PMN were introduced to directly
121 account for the mobility-related consequences of the personal living circumstances (e.g., having children, a
122 full-time job, complex daily routines) and turned out to improve the model fit when being added to a TPB
123 model as a predictor for the use of alternative transport modes to the car. In-depth interviews additionally
124 carried out in Haustein and Hunecke (2007) revealed that women with high PMN often had children and a job
125 outside home, and they felt a high necessity to escort their children by car to several activities. They perceived
126 it as impossible to switch from the car to public transport because of limited flexibility and long travel times.
127 In addition, their (or their children's) typical destinations were often located less central. A study by Shirgaokar
128 and Lanyi-Bennett (2019) also found that women's higher engagement in home-serving tasks (in addition to
129 paid work) and related time constraints is associated to more time spent driving. Constraints and demands
130 created by family and household responsibilities have also been identified as barriers of car use reduction in
131 studies on cycling (e.g., Bonham and Wilson, 2012; Pooley et al., 2013).

132 While it has been shown that PMN are related to socio-demographic variables, like having children or a job,
133 and to perceived time pressure, it so far remains unclear what exactly makes people perceive high mobility
134 needs and to what extent this is related to the structure of their specific daily activities. Besides, studies that
135 identified time restrictions and mobility needs as a barrier to increase cycling were conducted in low-cycling
136 countries. In Copenhagen and other cycling cities, where the bike is perceived as an effective transport mode
137 (Haustein et al., 2019a), it may have a similar function as the car, so that its use may increase with complexity
138 of everyday life.

1.2 The present study

This research is motivated by the need to better understand how, and to what extent, mode choice decisions are influenced by our everyday activities and their temporal, spatial or social constraints and the perception of these constraints. More specifically, we have the following hypotheses:

- (1) Commuters who have a more complex everyday life (indicated by the type of activities) are less likely to choose public transport, and more likely to select the car. Other than in low cycling countries, where cycling is hampered by family and household related demands (e.g. Pooley et al., 2013), we expect that a high number of activities in the cycling city of Copenhagen not only favours car use but also cycling.
- (2) The effect of the activities on mode choice is even stronger, when activities are characterised by temporal, spatial, social and/or compulsory constraints.
- (3) PMN are influenced both by the number of activities
- (4) and the activities' constraints.
- (5) Commuters with high PMN are more likely to choose individual transport modes (car and bike), and less likely to choose public transport.

To test these hypotheses, we use two rich data sources from Denmark. Section 2 reports a description of the datasets. We estimated an Integrated Choice and Latent Variable (ICLV) model, that consists of two components: a mode choice model, which is a function of the activity patterns, constraints and perceived mobility needs (as well as socio-demographic and level-of-service variables), and a latent variable model for the PMN, which is a function of both the complexity of the activity patterns and the constraints. Section 3 describes the model structure. We present the model results and provide a detail discussion in Section 4 and Section 5.

2 Data

2.1 Data sources

In this paper, we used two data sources. The first is the Danish National Travel Survey, *Transportvaneundersøgelsen* (TU; Christiansen, 2018). This dataset has been collected ongoing since 2006 with about 1000 interviews per month (approx. 80% by telephone and 20% on the internet), and currently consists of 150,000 individuals between 10-84 years of age. The survey is administered by the *Center for Transport Analytics* of the *Department of Technology, Management and Economics* at the *Technical University of Denmark*.

TU collects a full trip diary of all trips and (out-of-home) activities during a 24H period (starting and ending 3:00 a.m.), and collects information about trip length, departure time, travel time, mode, purpose at destination as well as area codes¹ at both ends of the trip. Furthermore, TU collects various background characteristics of the individual (socio-demographic-economic), the household (family members, location, and car ownership), the work place (location and parking facilities), as well as the transport possibilities (have a driver's license, holds a season pass, has a bike). More information about TU can be found in Christiansen and Warnecke (2018) and Christiansen and Skougaard (2015).

¹ Area codes are defined consistently with the zone system used in the Danish National Transport model.

The second data source, *Specialundersøgelsen* (SU), is a more in-depth survey, that was collected for a project on departure time modelling of commuting trips (Thorhauge, 2015). Data was collected first in 2013 and later again in 2017 to a pool of new respondents. This survey contains the same information as the TU-data (and is consistent with TU in terms of data structure and variable codes) but collected additional information about activity and trip constraints, latent variables as well as a stated choice experiment specifically designed to capture departure time preferences (the latter part is not relevant for this specific study).

The SU-data was collected directly at the workplaces among employees at universities, public organizations and private companies located in Copenhagen. Thus, the sample was designed specifically to target individuals who commute to work in the city during the morning rush hours and arrive at work between 6-10 a.m. The workplaces were selected based on their location and the amount of and diversity among employees. The five workplaces selected hold more than 16,500 employees, and there were no restrictions on which of the employees could participate. It is common to select the workplaces strategically when interviewing based on the destination (see for example the Santiago panel as described in Yáñez et al., 2010). The survey was distributed through emails containing a link to the online-questionnaire. More than 10,000 questionnaire links were distributed and 923 interviews were filled in, resulting in a response rate of almost 10%. More information on the data and data collection process can be found in Thorhauge et al. (Thorhauge et al., 2019, 2016).

In the following we will describe the parts unique to the SU-data, which are of relevance for this specific study. Firstly, a set of questions was defined to collect information about the flexibility of each trip reported in the trip diary and/or the activity tied to the specific trip. More specifically, following the typical literature in time geography (Hägerstrand, 1970) three types of constraints were considered: temporal, spatial and social constraints. Additionally, it was also considered whether the activity was compulsory or not. The four questions on constraints used in this specific study are presented in Table 1. More details on the trip chains and flexibility components can be found in Thorhauge et al. (2016).

201

Constraints	Questionnaire questions
1. <i>Spatial constraints:</i>	Could you have carried out this activity at another location? (yes/no).
2. <i>Temporal constraints:</i>	Were there any restrictions to how late you could have arrived? (yes/no ²)
3. <i>Social constraints:</i>	Did you decide yourself when to depart? (yes/partly/no)
4. <i>Compulsory constraints:</i>	Could you have omitted this trip/activity? (yes/no)

202 **Table 1:** Measures of constraints.

203 Secondly, 24 indicator statements were designed to capture various latent constructs thought to be relevant for
 204 transport related decisions (especially departure time, but also more general latent constructs). Of particular
 205 relevance for this study are three items operationalising the latent construct of Perceived Mobility Necessities
 206 as defined by Haustein and Hunecke (2007). The indicators were assessed on a 5-point Likert scale (Likert,
 207 1932) ranging from “totally disagree” (1), and to “totally agree” (5). The items are presented in Table 2.

Indicators	Mean	Std. Dev.	Skewness
1. The organization of my everyday life requires a high level of mobility	3.20	1.28	-0.18
2. I have to be mobile all the time to meet my obligations	3.11	1.32	-0.10
3. My work requires a high level of mobility	2.84	1.24	0.18

208 **Table 2:** Indicators for the latent variable *Perceived Mobility Necessities*. Chronbach’s alpha is 0.83.

² If they replied “yes”, we also asked what the latest possible arrival time was.

2.2 Level of service data

The datasets described above contain detailed information about (all) the trips individuals performed, such as mode, travel time, purpose, etc., but no information about non-chosen alternatives was available, which are necessary to estimate (mode) choice models.

In order to obtain Level-of-Service (LoS) for each respondent's non-chosen alternatives we relied on the Danish National Transport Model (Rich and Hansen, 2016). This is a 907-zone nationwide transport model consisting of 11 time periods and provides travel times, cost, and length among all combinations of OD-pairs for each mode and time period. Based on origin and destination of the trips reported by the respondents, we then joined the NTM-records with our data to obtain LoS-data for each trip in the sample. Time-of-day specific travel time (and length) is given directly from the NTM for each mode. For public transport, the Level-of-Service components in the NTM consist of in-vehicle time (*IVT*), (walk) transfer time (*TrT*) between e.g. a bus stop and a station platform, waiting time (*WT*), hidden waiting time (*HWT*), access-egress time (*AcEgT*) as well as the number of transfer (*#Tr*). The travel time for bike and walk in the NTM is computed as a function of the network length between OD-pairs, and it is assumed independent of the time-of-day, because congestion is rarely a relevant factor for the travel time by bike and walk.

The cost for car users consists of two parts. First of all, based on the network length provided by NTM a car-driving cost is computed assuming 0.85 DKK/km³, which reflects gasoline prices. Secondly, based on the trip destination we also joined our data with information about parking prices for the zones in Copenhagen, which enabled us to compute parking cost for the duration of the stay in that zone (if applicable for that zone). For public transport costs, we used ticket prices from origin (home) to destination (work) of the commuting journey. Ticket prices are conditional on whether individuals hold a season pass or not. For individuals not holding a season pass, we specified ticket prices equal to the cost of a single ticket. For individuals holding a season pass we converted the monthly season pass cost into an average cost for each trip, by dividing the price of the monthly ticket by the number of days per month individuals commute to work. In our data we know how many days per month individuals worked from home, which was used to compute the number of single trips (both outbound and homebound) over the course of a month (assuming 20 working days per month on average), which ultimately allowed us to compute the average cost per trip. We verified that for all individuals the computed cost was lower than the corresponding cost for a single ticket. Bike and walk alternatives are assumed to have no cost.

Finally, the LoS from the NTM were also used for the chosen mode, instead of the travel time and length reported by the respondents. This was done for two reasons: First, for consistency among level-of-services for the different modes. And second, because the travel times reported in the questionnaire are often overestimated (due to round-off or political bias). By relying on the NTM for both the chosen and non-chosen alternatives we avoid both issues.

2.3 Sample

The final sample used in this research consists of morning commuters travelling in the Greater Copenhagen Region, see Figure 1, between 6:00-10:00 A.M. using one of the following 5 modes: walking, cycling, car as driver, car as passenger or public transport (transit). The reason why we focussed on commuting trips into Copenhagen is because it makes the mode choice decision highly relevant due to congestion, in contrast to rural areas, where congestion (and lack of "appealing" alternatives to the car) is typically not present. We note that, despite the fact that TU is nationwide, we focus on the Greater Copenhagen Area, which ensures

³ Equivalent to 0.11 EUR/km.

geographical consistency with the SU dataset. The final sample consists of 10,784 individuals. Table 3a-c (in appendix) presents detailed descriptive statistics for the entire sample as well as grouped by dataset and mode. More specifically, it shows that 50.8 percent of the sample are women, while the average age is 37.7 (std. dev. = 15.3), the average income is 361,600 DKK (std. dev. = 289,200), and the average commuting distance to work is 12.6 km (std. dev. = 12.9). We also note that on average individuals carry out 3.6 activities per day. Furthermore, cyclists and car drivers have the highest number of daily activities (3.8 on average), followed by pedestrians and car passengers (on average 3.6 and 3.4 activities per day respectively), while public transport users are the group with the lowest number of daily activities (3.1 on average). We note a significant difference in the modes used between men and women, with men being more often car drivers, and women using more often other modes.

While TU-data are representative of the Danish (and hence Copenhagen) population, the same cannot be claimed for the SU-data (e.g. car drivers were deliberately oversampled); however, SU-data it is not significantly different from TU-data in some key areas (especially) relevant for this study, such as average commuting time and distance as well as proximity to public transport, number of cars in households, household size, working hours and income.

Finally, we defined the availability conditions for each mode as specified below:

$$Walking = \begin{cases} Walking \text{ is the chosen (observed) mode of transport} \\ or \\ Work \text{ within 5 km from home} \end{cases}$$

$$Cycling = \begin{cases} Cycling \text{ is the chosen (observed) mode of transport} \\ or \\ Respondent \text{ has a bike AND work within 25 km from home} \end{cases}$$

$$Car \text{ as driver} = \begin{cases} Car \text{ as driver is the chosen (observed) mode of transport} \\ or \\ Respondent \text{ has a drivers license AND car is accessible}^4 \end{cases}$$

$$Car \text{ as passenger} = \begin{cases} Car \text{ passenger is the chosen (observed) mode of transport} \\ or \\ Min 1 \text{ other adult in HH has a driv. license AND car is accesible}^4 \end{cases}$$

$$Public \text{ transport} = \begin{cases} Public \text{ transport is the chosen (observed) mode of transport} \\ or \\ Respondent \text{ has a public transport pass} \\ or \\ Station \text{ within 10 km from home} \end{cases}$$

Regarding the availability of car passengers, this information is not included in our dataset, so we cannot know exactly when this option is available (e.g. individuals could catch a ride with colleagues). It is our general understanding that catching a ride with a colleague is not very common in Denmark (possibly due to a fairly good coherent public transport system and a strong cycling culture providing good alternatives). We analysed the Danish National Transport Survey and found that less than 10% of commuting trips as car passengers were undertaken with colleagues, while more than 90% of all car passenger trips were done with a household member. Based on this, we decided to define the availability for the car passenger alternative as outlined above, rather than just setting the car passenger option to be available for everybody. Table 4 shows the distribution among modes for the two datasets, as well as how often each mode is available. We note an equal share for cyclists and car passengers. SU-data has a lower share of public transport usage and walking, while a higher share of car drivers. Table 5 shows the mean and standard deviation for the Level-of Service attributes among

⁴ car is assumed accessible if the household has at least one car or is a member of car sharing

278 available modes. Overall, the numbers look as expected, but we note a large standard deviation in car costs.
 279 This is because some respondents have to pay a high cost for (street) parking (dependent on the area) while
 280 others do not.
 281

	TU-data			SU-data			Total		
	Chosen	[%]	Available	Chosen	[%]	Available	Chosen	[%]	Available
Walking	676	[6.6%]	4,509	12	[2.1%]	174	688	[6.4%]	4,683
Cycling	3,426	[33.5%]	7,723	198	[35.0%]	444	3,624	[33.6%]	8,167
Car as driver	3,523	[34.5%]	6,091	289	[51.2%]	451	3,812	[35.3%]	6,542
Car as passenger	418	[4.1%]	6,710	13	[2.3%]	377	431	[4.0%]	7,087
Public transport	2,176	[21.3%]	10,210	53	[9.4%]	565	2,229	[20.7%]	10,775
Total	10,219	[100.0%]		565	[100.0%]		10,784	[100.0%]	

282 Table 4: Overview of the chosen and available modes.
 283

Mode	Walk	Bike	Car Driver	Car Passenger	Public Transport
Availability	N=4683	N=8167	N=6542	N=7087	N=10775
Travel Cost [DKK]			44.65 (63.22)	38.53 (60.00)	17.63 (14.32)
Travel Time [min]	26.65 (8.58)	23.46 (13.92)	22.12 (13.32)	19.24 (13.97)	16.91 (14.25)
Waiting Time [min]					0.73 (1.42)
Access/Egress Time [min]					15.9 (7.94)
Hidden Waiting Time (headway) [min]					5.77 (5.38)
Number of changes					0.41 (0.57)

284 Table 5: Mean and std. dev. of Level-of-Service attributes for all available modes.

285
 286 **Figure 1:** The study area was defined as the Greater Copenhagen Region. Only commuting trips with a final destination in the City of Copenhagen
 287 (dark grey area) were considered.

3 Mathematical model

This section describes the modelling framework and specifies the mathematical formulation. The purpose of the model is to explicitly account for mobility needs, activities and constraints. We operationalise perceived mobility necessities (PMN) as a latent variable, following the traditional hybrid choice model framework (Walker, 2001; Walker and Ben-Akiva, 2002), which consists of a choice model and a latent variable model. The Integrated Choice and Latent Variable (ICLV) model is estimated simultaneously across two datasets described in Section 2 (i.e. TU and SU data) and is depicted in Figure 2. This allows us to take advantages of the strengths of each dataset. Utilizing TU-data enables estimating more robust core parameters, such as Level-of-Service (LOS) attributes, socio-demographics, and activity patterns, as well as the alternative specific constants (ASC), while the SU enables estimating very detailed parameters regarding the latent variable PMN and activity constraints not possible with TU. As commonly done when estimating across two (or more) data sources, we append one dataset to the other, and account for the potential difference in scale by estimating a scale parameter.

Figure 2: Overview of the model framework for the Integrated Choice and Latent Variable model.

We hypothesize that PMN is influenced by two components: a measure of the complexity of the activity patterns (such as number of activities, distance travelled, etc.), and a measure of the level of individuals constraints. We expect that PMN will increase when the complexity (i.e. number of activities or distance travelled) of the activity pattern increases. Similar, we expect PMN to increase when the (temporal, spatial, spatial, compulsory) constraints level increases, since trips with a low constraint level (i.e. highly flexible) can

308 easier be re-scheduled, re-organized, re-planned or even cancelled and thus have a less “strict” influence on
 309 the perceived mobility necessities.

310 In turn, beside the common Level-of-Service attributes and individuals socio-demographic characteristics, we
 311 expect mode choice (for morning commute trips) to be influenced by activity patterns, constraints level and
 312 perceived mobility necessities. As highlighted in the introduction, we hypothesise that individuals with high
 313 perceived mobility necessities as well as many (different) types of activities performed in various times during
 314 the day will be more likely to select individual modes such as the car and the bike, that allow a higher
 315 flexibility, while individuals with simple activity patterns and highly flexible activities will be more likely to
 316 use public transport.

317

318 **3.1 Activity patterns and constraints**

319 As discussed in the literature review, the number of activities performed and the extent to which these are
 320 constrained, play a key role in the chosen transport mode. In order to capture this effect we use two aggregate
 321 measures. To capture the *activity complexity* we utilise the Shannon’s entropy measure, the same as used in
 322 Thorhauge et al. (2016). Shannon’s entropy measures the dispersion of activities (McBride et al., 2019, 2020;
 323 Scheiner, 2014) and it is defined as:

$$H = - \sum_{t=1}^T p_t \ln(p_t) \quad (1)$$

324 where p_t is the percentage of activities performed in each trip chain t . $H > 0$ means that activities are scattered
 325 across multiple trip chains, while $H = 0$ means that all activities are performed in a single trip chain. It is
 326 expected that individuals with scattered the activities, i.e. performed in different trip chains, are more likely to
 327 prefer and select individual modes, such as bike and car, in order to ease chained trips.
 328

329 The second aggregate measure is for the individuals’ level of constraints. All information about activity
 330 constraints (presented in Table 1) were recoded so that all have the same direction (i.e. 1 indicates a
 331 constraint in dimension c , while 0 indicates flexibility in dimension c):
 332

$$\gamma_c = \begin{cases} 1: \text{Constraint in dimension } c \\ 0: \text{Flexible in dimension } c \end{cases}$$

333

334 A constraint-score is then computed to obtain an overall aggregate constraint level:

$$\Gamma = \sum_{c=1}^C \gamma_c \mid \gamma_c = \{\text{Temporal, Spatial, Social, Compulsory activity constraints}\} \quad (2)$$

335 We used the constraint-score as an explanatory variable for both perceived mobility necessities and mode
 336 choice utility specification as depicted on Figure 2.

337

3.2 Perceived Mobility Necessities (PMN)

Perceived mobility necessities (PMN) is modelled as a latent variable. The structural model (2) and the measurement model (3), which the latent variable model, are specified as follows:

$$PMN_n = \alpha + \lambda_X \cdot X_n + \omega_n \quad (3)$$

Where

- PMN_n is the latent (unobservable) variable for individual n .
- X_n is the vector of explanatory observed covariates including the constraint score and number of activities while λ_X is the corresponding vector of unknown coefficients.
- α is the constant in the structural equation for the latent variable.
- ω_n is a normally distributed error term with zero mean and variance σ_ω .

The latent variable is specified using the set of $K=3$ indicators collected specifically for this purpose (see Table 2). The measurement equation for indicator k and individual n is defined according to the following expression:

$$I_{nk} = \delta_k + \theta_k \cdot PMN_n + v_{nk} \quad (4)$$

Where

- I_{nk} is the indicator k of the latent variable PMN for individual n .
- θ_k is the coefficient associated with the latent variable PMN for the indicator k .
- δ_k is the constant in the measurement equation for the indicator k .
- v_{nk} is a normally distributed error term with zero mean and variance σ_v .

3.3 Mode choice utility specification

The choice model includes 5 alternatives: walking, cycling, car as driver, car as passenger and public transport, where “car” stands for individual motorized modes. The systematic utility functions for the two dataset (SU and TU) are mostly identical, with the exception that the utility function for the SU-data also accounts for the data-specific elements of *activity constraints* and the latent *perceived mobility necessities* (PMN) that were collected (only) in the SU dataset. The systematic utility (V_{in}) that is common for both dataset is specified as follows:

$$V_{in} = ASC_i + \beta_i^{LoS} \cdot LoS_{in} + \beta_i^{Ent} \cdot Ent_n + \beta_i^{Act} \cdot Act_n + \beta_i^S \cdot S_n \quad (5)$$

Where

- ASC_i is the alternative specific constant for alternative i . The car alternative is defined as reference.
- LoS_{in} is a vector of Level-of-Service characteristics (such as travel time and cost) for each mode i and individual n , while β_i^{LoS} is a vector of corresponding parameters to be estimated.
- Ent_n is the aggregate measure of activity complexity (i.e. the Shannon’s Entropy) for individual n , while β_i^{Ent} is the corresponding parameter to be estimated.
- Act_n is a vector single activity dummies for individual n , while β_i^{Act} is a corresponding vector of parameters to be estimated.
- S_n is a vector of socio-demographic characteristics for individual n , while β_i^S is a corresponding vectors of parameters to be estimated.

Note that we decided to include the costs in the car passenger alternative as well. We did this because the vast majority of car passenger trips are done with household members as explained in Section 2.3, thus the cost is considered a joint household expense regardless of who is behind the wheel (In Denmark most households

380 make a joint decision on car ownership because of the high taxation, so expenses are most often assigned to
 381 the household budget). The overall utility specification is defined as:

$$\tilde{U}_{in}^{SU} = \tilde{V}_{in}^{SU} + \zeta \cdot (\varepsilon_{in}^{SU}) \quad (6)$$

$$\tilde{U}_{in}^{TU} = \tilde{V}_{in}^{TU} + \varepsilon_{in}^{TU} \quad (7)$$

$$\tilde{V}_{in}^{SU} = \zeta \cdot (V_{in}^{SU} + \beta_i^{\Gamma} \cdot \Gamma_n^{SU} + \beta_i^{PMN} \cdot PMN_n^{SU} + \eta_i \cdot \mu_{in}^{SU}) \quad (8)$$

$$\tilde{V}_{in}^{TU} = V_{in}^{TU} + \eta_i \cdot \mu_{in}^{TU} \quad (9)$$

382 Where:

- 383 - V_{in}^{SU} and V_{in}^{TU} are defined as in equation (4)
- 384 - Γ_n^{SU} is the constraint score for individual n , and β_i^{Γ} is the corresponding parameter to be estimated for
 385 alternative i .
- 386 - PMN is the latent Perceived Mobility Necessities for individual n , and β_i^{PMN} is the corresponding
 387 parameter to be estimated for alternative i .
- 388 - μ_{in}^{SU} and μ_{in}^{TU} are error components to account for uncaptured correlation between the two car
 389 alternatives, as well as random heterogeneity in the preferences for of the alternatives, while η_i are
 390 the associated coefficient to be estimated.
- 391 - ε_{in}^{SU} and ε_{in}^{TU} are the typical independent and identically distributed (i.i.d.) Extreme Value (EV) type 1
 392 error terms.
- 393 - ζ is a scale-parameter, to capture the potential difference in scale between the two data sources.

394

395 3.4 Model Estimation

396 Given the specifications of the utility functions described above, the conditional probability of individual n
 397 choosing mode i is given by:

$$CP_{in}^d = \frac{\exp(\tilde{V}_{in}^d)}{\sum_{j \in C_n^d} \exp(\tilde{V}_{jn}^d)} \quad \forall i, j \in C_n^d; d = \{SU, TU\} \quad (10)$$

398

399 The latent variable is only know to its distribution. Let Φ be the standard normal distribution function.
 400 Assuming independence among the LV (for simplicity), the distribution of the latent variable and the indicators
 401 are:
 402

$$f_{PMN_n} = \frac{1}{\sigma_{\omega}} \Phi \left(\frac{PMN_n - (\alpha + \lambda_X \cdot X_n)}{\sigma_{\omega}} \right) \quad (11)$$

$$f_{I_{nk}}(\omega) = \frac{1}{\sigma_{v_k}} \Phi \left(\frac{I_{nk} - (\delta_k + \theta_k \cdot PMN_n(\omega))}{\sigma_{v_k}} \right) \quad \forall k \in K \quad (12)$$

403

404 For the purpose of theoretical identification, we defined $\delta_l=0$ and $\theta_l=1$.

405

406

407 The unconditional joint probability is the integral of the conditional probability over the distribution of ω_{qm}
 408 and μ_{jn} . For the SU observations takes the expression:
 409

$$P_{in}^{SU} = \int_{\omega} \left(\int_{\mu} CP_{in}^{SU}(\mu_{in}^{SU}, \omega_n) f(\mu) d\mu \right) f_{PMN_n}(\omega) \prod_{k=1}^K f_{I_{nk}}(\omega) f(\omega) d\omega \quad (13)$$

410
 411 For the TU observations takes the expression:
 412

$$P_{in}^{TU} = \int_{\mu} CP_{in}^{TU}(\mu_{in}^{TU}) f(\mu) d\mu \quad (14)$$

413
 414 Let y_{in} be a matrix of individual choice indicators:
 415

$$y_{in} = \begin{cases} 1 & \text{if individuals } n \text{ selects alternative } i, \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

416
 417
 418 The log-likelihood function then is given by the logarithm of the product of the unconditional probabilities
 419 P_{in} :
 420

$$LL = \sum_n \sum_i y_{in} \ln(P_{in}^d) \quad d = \{SU, TU\} \quad (16)$$

421

422 4 Results

423 4.1 Model estimation

424 This section presents the modelling results. All model estimations were done using PythonBiogeme 2.5
 425 (Bierlaire, 2016). We estimated an integrated choice and latent variable (ICLV) model jointly across two RP-
 426 datasets containing a total of 10,784 observations (one observation per individual). The model contains 72
 427 parameters in total for both the choice and latent variable components and was estimated using 10,000 draws.
 428 The final log-likelihood is -10,055.021, while AIC is 20,260.041 and BIC is 20,806.478. The final parameters
 429 estimated for the choice model are presented in Table 7, while the parameters estimated for the latent variable
 430 model are presented in Table 6.

431 As described in the modelling section, our mode choice model includes several explanatory variables,
 432 including activity complexity, constraints and the latent variable Perceived Mobility Necessities (PMN), other
 433 than alternative specific Level-of-Service attributes and individuals' background characteristics. Overall, we
 434 note that all parameters estimated for the level-of-service attributes are negative and significant (at least) at
 435 95% confidence level. We tested for income effects, but did not find them to be significant. To account for
 436 cost-damping effects, we applied a Box-Cox transformation for the travel cost and found the associated Box-
 437 Cox-parameter to be significantly different from a linear assumption. For completeness, we also tested for non-
 438 linear effects for the time components but did not find any cost-damping effects to be significant. The estimated

average value of (in-vehicle) time (VOT) is 127.76, 104.74, and 44.17 DKK/hour for car drivers, car passengers, and public transport users, respectively. For comparison, the average VOT in a Danish context is found to be 121 DKK/hour while being 93 DKK/hour for the commuter segment (Fosgerau et al., 2007; Modelcenter, 2019). With respect to gender preferences, as expected, males are more likely to use the car (as driver), while females are more likely to use all other modes.

In line with Hypothesis 1, we included various dummies, to reflect if individuals engaged in certain activities during different periods of the day. We found that all parameters associated to these dummies (except the parameter for escorting activities performed in the morning by car) are positive, indicating that if individuals are engaging in escort, errand and/or leisure activities either during home-work commute, work-home commute and/or in the evening after returning back home from work, then they are more likely to use other modes than public transport. We believe this is due to the nature of timetable-based transport modes since every new activity involves access/egress trips as well as waiting time at every stop, making it a slow and inefficient way to facilitate complex activity patterns. Furthermore, we found that the entropy measure is positive and significant for the bike and car driver alternatives, indicating that the more activities are dispersed across multiple trip chains the more likely individuals are to use these two modes. This is also in line with Hypothesis 1, i.e. individuals with (more) complex activity patterns are more likely to use individual modes, such as car and bike.

In addition to that, we found that individuals who are constrained in their activities during the morning commute are less likely to use public transport (and thereby more likely to use individual modes), which confirms Hypothesis 2. Furthermore, we found that individuals with high(er) degree of PMN favour individual modes of transportation, such as car and bike, as these makes it relatively easier to get around and engage in various activities. This confirms Hypothesis 3.

The latent variable PMN is influenced by two (observable) components: the number of daily activities performed by the individuals, and a constraint-score that captures how constrained individuals are during the commute trip from home to work. We found that PMN increases as both the number of activities and the constraint-level increase, which confirms Hypotheses 4 and 5. The fact that PMN increases with individuals' constraint-level is reasonable because inflexible activities cannot be rescheduled, changed and/or cancelled, thus the (perceived) need for mobility is higher, oppose to flexible activities, which can be altered or cancelled, thereby making the (perceived) need for mobility less strict. In line with the existing literature, we also tested various socio-demographics (in particular related to the presence of children and the need of escorting them to/from activities) as explanatory variables for PMN, as well as including the total distance travelled in order to represent a spatial element of their activity pattern, but found none of these effects to be significant when also including the number of activities and constraints as explanatory variables. Since PMN has a positive impact on the utility for car drivers and cyclists, it means that individuals who have many daily activities and/or have a high level of constraints are more likely to select car or bike to address their needs and engage in activities. This is consistent and in line with direct effects confirmed for Hypothesis 1 and 2 above.

	Value	t-test
Structural Equation		
Intercept	<i>2.690</i>	<i>14.920</i>
Number of daily activities	<i>0.078</i>	<i>2.280</i>
Constraint-score	0.103	1.730
Sigma	<i>1.040</i>	<i>22.930</i>
Measurement equations		
<i>Indicator 1</i>		
Std. Dev.	0.722	13.680
<i>Indicator 2</i>		
Intercept	-0.100	-0.490
LV coeff.	1.000	17.000
Std. Dev.	0.794	15.590
<i>Indicator 3</i>		
Intercept	0.089	0.520
LV coeff.	0.859	15.350
Std. Dev.	0.839	19.340

Table 6: parameter estimates for Latent variable model for Perceived Mobility Necessities (PMN). Parameters in italic: P<0.05. The constraint score is computed as a sum of the following four constraints variables, which represents temporal, spatial, social, and compulsory constraints: 1) Did you have any constraints in terms of how late you could arrive? 2) Could you have performed this activity at another location? 3) Did you decide yourself when to depart? 4) Could you have omitted this activity?

	Walk		Bike		Car driver		Car passengers		Public Transportation		Multiple modes	
	Value	t-test	Value	t-test	Value	t-test	Value	t-test	Value	t-test	Value	t-test
Level-of-Service, ASC, scale, and error components												
ASC	6.590	8.850	2.340	3.770			-4.160	-3.680	-0.076	-0.100		
Travel Time [1/min]	-0.366	-15.110	-0.280	-12.920	-0.064	-5.920	-0.048	-3.400	-0.046	-3.880		
Waiting Time [1/min]									-0.182	-2.710		
Access/Egress Time [1/min]									-0.051	-3.640		
Hidden Waiting Time (Headway) [1/min]									-0.100	-4.760		
Number of changes									-0.395	-2.410		
Travel Cost for car driver, car passenger and public transport [1/DKK]											-0.833	-5.800
BoxCox parameter for Travel Cost (T-test against 1)											0.092	-28.854
Scale between TU & SU data (T-test against 1)											0.937	-0.327
Error Component - Std. Err of ASC			2.040	7.020			3.290	4.190				
Error Component - car driver & car passenger											2.720	4.490
Socio-demographics												
Household has 1 car					-1.270	-2.240						
Household has 2+ cars					1.260	2.150						
Parking available at work					1.370	5.050						
Parking free at work					1.040	4.610						
Age < 30	0.403	1.970					1.090	2.440	0.433	3.110		
Age >= 50							0.702	2.300				
Male	-0.659	-3.210	-0.457	-2.520			-2.300	-5.120	-0.841	-4.620		
Education, University degree	0.680	2.700	1.700	7.400					0.860	4.060		
Education, Elementary school							0.583	1.440	0.781	3.980		
Education, High school			0.878	4.010					1.020	4.410		
Work hours per week = 37H			0.725	4.330					0.487	3.270		
Work hours per week < 37 H	0.721	2.530	1.230	4.610					1.300	4.930		
Activities and constraints												
Entropy			0.587	2.49	1.04	3.73						
Has Errand activity - Home-Work	4.300	2.550	1.600	2.220			2.120	2.450				
Has Errand activity - Work-Home					1.150	4.590	1.360	3.470				
Has Errand activity - After-Work			0.534	3.500								
Has Escort activity - Home-Work	4.110	6.340	0.714	2.300	-0.722	-2.500						
Has Escort activity - Work-Home					0.853	3.410	0.870	2.350				
Has Escort activity - After-Work												
Has Leisure activity - Home-Work	5.110	5.160										
Has Leisure activity - Work-Home			0.587	3.930	0.822	3.240						
Has Leisure activity - After-Work	0.323	1.980	0.543	4.140								
<i>Only estimated using SU-data (information not available in TU)</i>												
LV PMN			0.269	1.910	0.289	2.010						
Constraint-score									-0.356	-2.270		

Table 7: Mode choice model parameter estimates. Parameters in italic: $P < 0.05$. The constraint score is computed as a sum of the following four constraints variables, which represents temporal, spatial, social, and compulsory constraints: 1) Did you have any constraints in terms of how late you could arrive? 2) Could you have performed this activity at another location? 3) Did you decide yourself when to depart? 4) Could you have omitted this activity?

4.2 Policy scenario: forecasting implication of a Toll Ring

The estimated mode choice model allows us to forecast the effect of policy scenarios. In line with the increased congestion and higher environmental awareness, many cities are looking into raising the level of service of their transit system. One effective solution is to implement designated bus lanes or signal prioritization, to avoid having the busses being stuck in traffic. Prioritizing busses often results in increased travel times for car commuters due to either less capacity (e.g. by converting a car lane into a designated bus lane) or shorter green light cycles. To mimic such a policy scenario, in our forecasting simulation we assumed that the travel time for bus decreased by 20% while the travel time for cars increased by 20%. Furthermore, we assumed that the time-of-day and the destination of the trips remain constant, since modelling such changes would require a full transport model, which is beyond the scope of this paper. This assumption is of course not realistic, but nevertheless useful for the purpose of illustrating the behavioural insights our model provides.

In this forecast, we only utilize the individuals from the SU-data, since we are mainly interested in understanding the effect of how (complexity of) activities, constraints and (perceived) mobility influence the mode choice, which (for the latter two) are only available in this dataset. Figure 3 presents the substitution patterns as a result of implementing a policy scenario in which public transport is prioritized. The horizontal line shows the substitution pattern for the entire SU-data sample, and we note that the car alternatives loses market shares, while the public transport and bike alternatives gain market shares. Furthermore, we segmented the sample based on their level of Perceived Mobility Necessities (PMN) into three segments based on the tertiles. Thus, the first group consists of the bottom third of individuals with the lowest PMN, while the second group consists of the middle third of individuals with medium PMN (centred around the median), and the third and last group consists of the top third of individuals with the highest PMN. We see a distinct difference in how the three segments react to the implementation of such a policy scenario. Interestingly, among individuals who shifted away from car we note that in the segment with the lowest PMN, approx. 90% shifted to public transport, while only 10% shifted to bike. However, in the segment with the highest PMN, approx. 60% shifted to public transport, while 40% shifted to bike. This is in line with our hypothesis that individuals with high mobility needs prefer individual modes and avoid public transport. Thus, if car users are to change transport mode, those with more complex activity patterns and higher mobility needs are more likely to shift to bike (as compared to other groups).

Figure 3: Overview of the model framework for the Integrated Choice and Latent Variable model.

5 Discussion and Conclusions

Shifting people's transport choices from private motorised modes to more environmentally friendly modes has been attempted with various hard and soft measures but so far turned out to be a very challenging task. One reason for this has been identified as the need to coordinate constrained activities (e.g. escorting children and commuting to work), which for some people makes it impossible (or at least very unattractive) not to use the private car (e.g., Pooley et al., 2013). In this paper, we looked in more details into the role of activity patterns, related constraints and mobility needs both from an objective and subjective perspective and how these factors influence the mode choice of commuters in Copenhagen. We expected that activity constraints and perceived mobility needs do not only advance car use but also cycling, as citizens in Copenhagen (compared to people in low-cycling cities) perceive the bike as a fast and efficient transport mode (Haustein et al., 2019a).

To analyse mode choice decisions for morning commuters in Greater Copenhagen, we estimated an Integrated Choice and Latent Variable (ICLV) model. We explicitly accounted for the complexity of activity patterns, constraints during the morning commute, and the latent variable of Perceived Mobility Necessities (PMN). More specifically, in the choice model we accounted for the entropy of individuals' activities as well as various types of activities (escort, errand, and leisure) during different time-of-day periods (morning, afternoon, and evening). Furthermore, we accounted for the role of constraints through an aggregate measure of constraints in various dimensions (temporal, spatial, social, and compulsory). We found that people with (more) complex activity patterns, a high(er) degree of constraints and a high(er) level of PMN are more likely to select

individual modes, such as car and bike, while they are less likely to select public transport. This is strengthened by the fact that PMN increased with both the number of activities and the constraints individuals encounter during their commute. These findings confirm our five hypotheses. We believe this is due to the fact that public transport is a relatively rigid (and sometimes unreliable) mode of transportation, and thus would better suit individuals with less complex activity patterns and more flexible schedules as they can adapt to the predefined timetables and stopping locations of public transport (all else equal). Through a policy analysis simulating public transport prioritization, we showed that a higher share of individuals with high PMN shift from car to bike (rather than to public transport) compared to individuals with lower PMN. This result supports our hypothesis that in Copenhagen the bike is regarded as a time-efficient alternative to the car.

While we expect that this finding is transferable to other cities with a distinct cycling culture, in particular cities in the Netherlands (Carstensen and Ebert, 2019; Haustein et al., 2019b; Nello-Deakin and Nikolaeva, 2020), the bike does not play a relevant role as an alternative to the car in low-cycling countries. Thus, in low-cycling countries the relation we found between complex activity patterns, perceived mobility needs and the use of individual modes, is probably restricted to car use. Yet, the result that the bike can have a similar function as the car (at least for short distant trips), may encourage other cities to invest in better conditions for cycling. It is also likely that in southern European cities (e.g., in Greece or Italy), other individual modes, in particular mopeds and motorcycles, can play a similar roles as the bike does in Copenhagen or Amsterdam.

With regard to gender, we found that men are more likely to use car as a driver, while women are more likely to choose all other modes, which resembles earlier findings based on TU-data and might reflect different gender roles determining who is sitting on the driver seat and/or different modal preferences (Haustein et al., 2014). However, this result is in conflict with a recent Canadian study according to which women drive more than men as a result of more mandatory trips for both paid and unpaid work and related time constraints (Shirgaokar and Lanyi-Bennett, 2019). A reason for the conflictive results might be that car ownership in Copenhagen is generally lower than in Canada and having two cars in the household is more often the exception. In addition, cycling is often an alternative to the car, which is – other than in low-cycling countries – more often chosen by women than men (Haustein et al., 2019a).

Structural improvements that ease the handling of a complex everyday life and raise flexibility are, according to our results, likely to decrease car use. Such measures include for example more flexible working and day care times, day care close to the workplace, or escorting services for children, such as “walking school busses” (e.g. Kingham and Ussher, 2007). In Denmark, like in other countries where household tasks are divided more equally among genders, such measures would not only support women, but families in general as well as single parents, who often cannot afford a car, in particular.

Although the findings from our behavioural analysis show that perceived mobility necessities, individuals’ activities and their constraints are important factors for modal choices, these factors are usually not included in larger datasets. While this restricts the use for large scale policy analysis today, it may encourage the future inclusions of selected variables, for example in national travel surveys.

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582 **Author contributions**

583 Survey development and data collection was undertaken by Mikkel Thorhauge, Elisabetta Cherchi and Sonja
584 Haustein. The model design, estimation and analysis was performed by Mikkel Thorhauge and Habtamu
585 Tilahun Kassahun, and supervised by Elisabetta Cherchi. The manuscript was drafted by Mikkel Thorhauge
586 and critically revised by Habtamu Tilahun Kassahun, Elisabetta Cherchi and Sonja Haustein. All authors read
587 and approved the final manuscript.

588

589 **Compliance with ethical standards**

590 **Conflict of interest**

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

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Appendix with Tables

Table 3a: Socio-demographics

		Walk (6.4%)		Bike (33.6%)		Car Driver (35.3%)		Car Passenger (4%)		Public Transport (20.7%)		All modes (100%)		Total Sample
		TU	SU	TU	SU	TU	SU	TU	SU	TU	SU	TU	SU	
<i>N</i>		676	12	3,426	198	3,523	289	418	13	2,176	53	10,219	565	10,784
Gender	Male	47.9%	41.7%	45.1%	57.6%	57.8%	49.8%	31.6%	0.0%	45.2%	45.3%	49.1%	50.8%	49.2%
	Female	52.1%	58.3%	54.9%	42.4%	42.2%	50.2%	68.4%	100.0%	54.8%	54.7%	50.9%	49.2%	50.8%
Age	< 30	70.1%	16.7%	43.1%	8.6%	8.7%	2.8%	50.7%	30.8%	39.3%	9.4%	32.5%	6.4%	31.1%
	30-59	17.2%	66.7%	38.6%	61.6%	56.2%	56.1%	27.3%	15.4%	39.0%	47.2%	42.9%	56.5%	43.6%
	50 +	12.7%	16.7%	18.3%	29.8%	35.1%	41.2%	22.0%	53.8%	21.6%	43.4%	24.6%	37.2%	25.3%
	<i>mean</i>	24.6	41.1	33.5	43.4	45.0	46.8	31.1	45.9	35.8	45.5	37.3	45.3	37.7
	<i>std. dev.</i>	16.2	9.8	15.3	11.2	10.9	10.5	18.5	15.5	14.9	12.7	15.4	11.2	15.3
Education	Elementary school	61.7%	0.0%	26.9%	0.0%	5.7%	0.3%	47.8%	0.0%	21.8%	1.9%	21.7%	0.4%	20.5%
	High school	7.2%	0.0%	10.8%	3.5%	8.9%	1.4%	6.9%	0.0%	16.3%	1.9%	10.9%	2.1%	10.5%
	Vocational	6.8%	0.0%	9.2%	0.0%	24.2%	6.6%	13.9%	0.0%	13.5%	1.9%	15.3%	3.5%	14.7%
	University	24.3%	100.0%	53.1%	96.5%	61.1%	91.7%	31.3%	100.0%	48.4%	94.3%	52.1%	94.0%	54.3%
Individual income (1000 DKK)	Low (<200)	50.1%	8.3%	28.7%	2.5%	3.3%	2.4%	40.9%	15.4%	20.0%	1.9%	20.0%	2.8%	19.1%
	Medium (200–400)	16.3%	33.3%	27.7%	27.8%	30.6%	21.5%	24.4%	23.1%	27.5%	32.1%	27.8%	25.0%	27.6%
	High (>400)	9.0%	41.7%	23.5%	61.6%	45.7%	65.7%	18.2%	38.5%	25.2%	52.8%	30.3%	61.9%	32.0%
	Unknown	24.6%	16.7%	20.1%	8.1%	20.4%	10.4%	16.5%	23.1%	27.3%	13.2%	21.9%	10.3%	21.3%
	<i>mean</i>	141.1	445.7	286.1	489.7	485.8	552.8	217.5	476.3	322.0	470.5	351.1	520.4	361.6
	<i>std. dev.</i>	224.2	290.7	258.6	199.0	314.6	231.4	228.9	290.2	217.5	188.3	290.1	221.6	289.2
Work hours per week	<37	9.3%	0.0%	13.2%	7.1%	13.5%	9.0%	11.0%	30.8%	13.8%	11.3%	13.1%	8.8%	12.8%
	37	17.0%	25.0%	35.8%	36.4%	48.4%	30.1%	28.0%	15.4%	37.7%	49.1%	39.0%	33.6%	38.7%
	>37	10.2%	66.7%	16.3%	53.0%	34.3%	60.6%	13.6%	30.8%	17.5%	35.8%	22.2%	55.0%	24.0%
	Unknown	63.5%	8.3%	34.7%	3.5%	3.9%	0.3%	47.4%	23.1%	31.1%	3.8%	25.7%	2.5%	24.5%
	<i>mean</i>	37.2	42.4	37.1	41.0	39.0	41.9	37.0	38.6	37.0	38.8	37.9	41.2	38.2
	<i>std. dev.</i>	8.3	6.5	6.1	8.6	7.6	8.4	6.8	9.8	6.1	5.9	7.0	8.3	7.1
Number of cars	0 cars	36.1%	58.3%	38.7%	42.4%	1.6%	0.3%	6.0%	0.0%	38.6%	28.3%	24.4%	18.9%	24.1%
	1	50.4%	41.7%	50.2%	51.5%	55.0%	55.4%	63.9%	69.2%	49.9%	66.0%	52.4%	55.0%	52.5%
	2+	13.5%	0.0%	11.1%	6.1%	43.4%	44.3%	30.1%	30.8%	11.5%	5.7%	23.3%	26.0%	23.4%
	<i>mean</i>	0.8	0.4	0.7	0.6	1.5	1.6	1.3	1.5	0.7	0.8	1.0	1.1	1.0
	<i>std. dev.</i>	0.7	0.5	0.7	0.6	0.6	1.8	0.6	0.8	0.7	0.5	0.8	1.4	0.8
Member of carshare	Yes	0.6%	0.0%	1.4%	0.0%	0.3%	0.0%	0.0%	0.0%	0.8%	0.0%	0.8%	0.0%	0.8%
	No	30.3%	66.7%	63.3%	86.9%	99.3%	99.7%	46.9%	92.3%	65.9%	86.8%	73.4%	93.1%	74.4%
	Unknown	69.1%	33.3%	35.3%	13.1%	0.4%	0.3%	53.1%	7.7%	33.2%	13.2%	25.8%	6.9%	24.8%
Has driver's license	Yes	30.9%	66.7%	64.7%	86.9%	99.6%	99.7%	46.9%	92.3%	66.8%	86.8%	74.2%	93.1%	75.2%
	No	69.1%	33.3%	35.4%	13.1%	0.4%	0.3%	53.1%	7.7%	33.2%	13.2%	25.8%	6.9%	24.8%
Has season ticket	Yes	14.8%	66.7%	10.9%	38.4%	8.0%	36.3%	21.8%	69.2%	77.4%	98.1%	24.8%	44.2%	25.8%
	No	85.2%	33.3%	89.1%	61.6%	92.0%	63.7%	78.2%	30.8%	22.6%	1.9%	75.2%	55.8%	74.2%
Has bicycle	Yes	78.3%	66.7%	99.9%	100.0%	71.1%	90.3%	79.4%	84.6%	77.0%	88.7%	82.8%	92.9%	83.3%
	No	21.7%	33.3%	0.1%	0.0%	28.9%	9.7%	20.6%	15.4%	23.0%	11.3%	17.2%	7.1%	16.7%

Table 3b: Travel characteristics

		Walk (6.4%)		Bike (33.6%)		Car Driver (35.3%)		Car Passenger (4%)		Public Transport (20.7%)		All modes (100%)		Total Sample
		TU	SU	TU	SU	TU	SU	TU	SU	TU	SU	TU	SU	
<i>N</i>		676	12	3,426	198	3,523	289	418	13	2,176	53	10,219	565	10,784
Parking at work	Always/normally Available	17.9%	8.3%	17.6%	14.1%	6.1%	5.5%	14.8%	15.4%	20.2%	30.2%	14.1%	11.2%	14.0%
	Rarely/never available	53.7%	50.0%	60.0%	62.6%	90.4%	93.8%	74.6%	76.9%	59.1%	58.5%	70.5%	78.2%	70.9%
	Free parking	12.3%	0.0%	15.7%	23.7%	6.9%	8.7%	11.5%	15.4%	23.6%	35.8%	13.9%	16.5%	14.1%
	Paid parking	59.3%	58.3%	61.9%	53.0%	89.7%	90.7%	78.0%	76.9%	55.7%	52.8%	70.7%	72.9%	70.8%
	Unknown	28.4%	41.7%	22.4%	23.2%	3.4%	0.7%	10.5%	7.7%	20.7%	11.3%	15.4%	10.6%	15.2%
Commuting time to work (min)	>15	53.6%	16.7%	22.7%	4.5%	7.1%	1.0%	27.8%	0.0%	0.3%	0.0%	14.8%	2.5%	14.2%
	15-25	31.5%	25.0%	35.4%	34.3%	26.1%	12.8%	30.4%	15.4%	7.2%	3.8%	25.7%	19.8%	25.4%
	25-35	9.2%	50.0%	24.4%	34.3%	25.4%	31.1%	19.1%	46.2%	18.8%	11.3%	22.3%	31.2%	22.8%
	35-45	3.1%	8.3%	11.5%	15.7%	19.6%	18.3%	9.8%	15.4%	22.0%	13.2%	15.9%	16.6%	16.0%
	45-55	1.9%	0.0%	4.2%	8.1%	12.6%	16.6%	8.1%	7.7%	21.2%	22.6%	10.7%	13.6%	10.9%
	55+	0.7%	0.0%	1.8%	3.0%	9.2%	20.1%	4.8%	15.4%	30.5%	49.1%	10.5%	16.3%	10.8%
	<i>mean</i>	10.4	17.7	17.5	22.8	26.9	35.2	19.4	34.1	42.4	48.5	25.7	31.7	26.0
	<i>std. dev.</i>	9.8	8.1	11.5	11.9	15.8	19.1	17.2	22.3	18.3	16.9	17.9	18.4	18.0
Commuting distance to work (km)	0-10	99.9%	100.0%	90.1%	85.4%	29.2%	24.2%	55.0%	46.2%	35.5%	15.1%	56.7%	46.9%	56.2%
	11-20 km	0.1%	0.0%	9.3%	13.1%	30.4%	30.4%	25.4%	15.4%	32.2%	32.1%	21.5%	23.5%	21.6%
	21-30	0.0%	0.0%	0.4%	1.0%	18.5%	19.7%	8.1%	23.1%	16.0%	15.1%	10.3%	12.4%	10.4%
	31-40	0.0%	0.0%	0.1%	0.5%	11.6%	11.8%	6.9%	7.7%	8.6%	24.5%	6.2%	8.7%	6.3%
	41-50	0.0%	0.0%	0.0%	0.0%	6.2%	9.3%	2.6%	0.0%	4.9%	9.4%	3.3%	5.7%	3.4%
	More than 50	0.0%	0.0%	0.0%	0.0%	4.1%	4.5%	1.9%	7.7%	2.8%	3.8%	2.1%	2.8%	2.1%
	<i>mean</i>	1.1	1.8	4.6	6.1	19.1	21.3	12.2	17.8	17.5	24.0	12.4	15.8	12.6
	<i>std. dev.</i>	1.3	1.8	3.8	4.5	14.0	15.1	12.7	16.6	12.9	13.1	12.8	14.3	12.9
Distance to nearest station (km)	0-1 km	76.3%	83.3%	67.6%	80.3%	48.6%	45.0%	52.2%	53.8%	63.5%	66.0%	60.1%	60.4%	60.1%
	1-2 km	19.5%	16.7%	27.7%	17.2%	32.7%	34.3%	32.1%	23.1%	27.9%	26.4%	29.1%	26.9%	29.0%
	2-3 km	2.8%	0.0%	3.4%	2.5%	9.1%	10.0%	8.6%	7.7%	5.1%	5.7%	5.9%	6.7%	6.0%
	3-4 km	0.4%	0.0%	0.4%	0.0%	2.6%	3.8%	2.2%	15.4%	1.0%	0.0%	1.4%	2.3%	1.4%
	4-5 km	0.9%	0.0%	0.6%	0.0%	3.2%	2.1%	1.4%	0.0%	1.2%	1.9%	1.7%	1.2%	1.6%
	5+	0.0%	0.0%	0.3%	0.0%	3.9%	4.8%	3.6%	0.0%	1.2%	0.0%	1.8%	2.5%	1.9%
	<i>mean</i>	0.8	0.6	0.9	0.7	1.4	1.5	1.3	1.3	1.0	0.9	1.1	1.1	1.1
	<i>std. dev.</i>	0.6	0.4	0.6	0.4	1.3	1.5	1.2	1.2	0.9	0.7	1.0	1.2	1.0

Table 3c: Activity patterns

		Walk (6.4%)		Bike (33.6%)		Car Driver (35.3%)		Car Passenger (4%)		Public Transport (20.7%)		All modes (100%)		Total Sample
		TU	SU	TU	SU	TU	SU	TU	SU	TU	SU	TU	SU	
<i>N</i>		676	12	3,426	198	3,523	289	418	13	2,176	53	10,219	565	10,784
Number of (out-of-home) activities	1-2 act	34.0%	50.0%	29.9%	42.4%	31.7%	38.8%	38.8%	30.8%	47.5%	47.2%	34.9%	40.9%	35.2%
	3-4 act	42.9%	41.7%	44.0%	37.9%	40.3%	46.0%	41.6%	38.5%	38.2%	45.3%	41.4%	42.8%	41.4%
	5-6 act	17.8%	8.3%	19.9%	14.6%	19.0%	12.8%	15.3%	15.4%	11.9%	5.7%	17.6%	12.7%	17.3%
	7-8 act	3.8%	0.0%	4.4%	4.5%	5.9%	2.4%	3.3%	15.4%	2.0%	1.9%	4.3%	3.4%	4.3%
	9+ act	1.5%	0.0%	1.8%	0.5%	3.0%	0.0%	1.0%	0.0%	0.4%	0.0%	1.8%	0.2%	1.8%
	<i>mean</i>	3.7	2.8	3.8	3.3	3.8	3.2	3.4	3.9	3.1	2.9	3.7	3.2	3.6
	<i>std. dev.</i>	1.7	1.0	2.6	1.6	1.9	1.4	1.6	1.9	1.4	1.2	2.1	1.4	2.1
Has escort activity - Home-Work (HW)	Yes	1.5%	16.7%	5.6%	13.6%	12.6%	14.5%	5.7%	7.7%	4.5%	13.2%	7.5%	14.0%	7.9%
	No	98.5%	83.3%	94.4%	86.4%	87.4%	85.5%	94.3%	92.3%	95.5%	86.8%	92.5%	86.0%	92.1%
Has errand activity - Home-Work (HW)	Yes	0.1%	8.3%	0.9%	1.0%	1.3%	2.1%	2.2%	0.0%	0.7%	0.0%	1.0%	1.6%	1.0%
	No	99.9%	91.7%	99.1%	99.0%	98.7%	97.9%	97.8%	100.0%	99.3%	100.0%	99.0%	98.4%	99.0%
Has Leisure activity - Home-Work (HW)	Yes	0.4%	0.0%	0.4%	1.0%	0.9%	1.0%	0.7%	0.0%	0.5%	0.0%	0.6%	0.9%	0.6%
	No	99.6%	100.0%	99.6%	99.0%	99.1%	99.0%	99.3%	100.0%	99.5%	100.0%	99.4%	99.1%	99.4%
Has escort activity - Work-Home (WH)	Yes	1.9%	8.3%	6.0%	8.6%	12.5%	17.0%	4.8%	23.1%	4.2%	9.4%	7.5%	13.3%	7.8%
	No	98.1%	91.7%	94.0%	91.4%	87.5%	83.0%	95.2%	76.9%	95.8%	90.6%	92.5%	86.7%	92.2%
Has errand activity - Work-Home (WH)	Yes	9.0%	0.0%	14.2%	8.1%	17.7%	14.2%	14.4%	15.4%	11.4%	17.0%	14.5%	12.0%	14.3%
	No	91.0%	100.0%	85.8%	91.9%	82.3%	85.8%	85.6%	84.6%	88.6%	83.0%	85.5%	88.0%	85.7%
Has Leisure activity - Work-Home (WH)	Yes	16.3%	8.3%	16.7%	11.6%	10.1%	10.4%	15.8%	23.1%	11.2%	5.7%	13.2%	10.6%	13.1%
	No	83.7%	91.7%	83.3%	88.4%	89.9%	89.6%	84.2%	76.9%	88.8%	94.3%	86.8%	89.4%	86.9%
Has escort activity - After Work (AW)	Yes	3.1%	0.0%	4.8%	3.5%	7.9%	2.4%	4.1%	0.0%	3.5%	1.9%	5.5%	2.7%	5.3%
	No	96.9%	100.0%	95.2%	96.5%	92.1%	97.6%	95.9%	100.0%	96.5%	98.1%	94.5%	97.3%	94.7%
Has errand activity - After Work (AW)	Yes	11.1%	0.0%	13.3%	13.6%	11.6%	3.5%	8.4%	0.0%	8.4%	3.8%	11.3%	6.9%	11.1%
	No	88.9%	100.0%	86.7%	86.4%	88.4%	96.5%	91.6%	100.0%	91.6%	96.2%	88.7%	93.1%	88.9%
Has Leisure activity - After Work (AW)	Yes	33.3%	8.3%	28.3%	14.1%	20.3%	10.7%	23.9%	30.8%	18.4%	9.4%	23.6%	12.2%	23.0%
	No	66.7%	91.7%	71.7%	85.9%	79.7%	89.3%	76.1%	69.2%	81.6%	90.6%	76.4%	87.8%	77.0%