Innovative pricing policies for commuting: a field experiment

Working paper: 2018/Dec/15

Stephan Lehner[a,*], Stefanie Peer[a], Mateusz Gren[b], Hannes Koller[c], Melitta Dragaschnig[c], Norbert Brändle[c], Raja Sengupta[d]

[a]*Department of Socioeconomics, Vienna University of Economics and Business, Welthandelsplatz 1, 1020 Vienna, Austria*
[b]*Mateusz Gren e.U., Lechnerstrasse 1-5, 1030 Vienna, Austria*
[c]*Austrian Institute of Technology, Giefinggasse 4, 1210 Vienna, Austria*
[d]*Department of Civil and Environmental Engineering, University of California, Berkeley, CA 94709, USA*

Abstract

Based on an innovative field experiment, this paper analyzes the effect of spatially and temporally differentiated pricing instruments on the travel behavior of commuters. The study aims to understand the underlying preferences, trade-offs, and restrictions faced by participants. The experiment uses a smartphone-based tracking technology performing automatic detection of travel modes. We recruited volunteers commuting by car to Vienna (Austria). A dedicated app recorded the commuting behavior of 95 participants throughout five weeks, including a week of pre- and post-measurement, respectively. Only a few participants changed their behavior in the expected direction. Plausible reasons are the experiment's innovative design, as well as, inconvenience related to adjusting one's schedule and mode of transport, in particular altering one's start of work.

Keywords: field experiment, travel data collection, travel behavior analysis, travel survey methods, parking pricing, road pricing (5-10 keywords)

*Corresponding author: `stlehner@wu.ac.at` (Stephan Lehner)

1. Introduction

During peak hours and along the main routes, the travel time of people communing to Vienna (Austria) increases by about 50% compared to free flow conditions (TOMTOM, 2017). The resulting welfare losses due to travel time increases, schedule delays, and environmental externalities are substantial. We seek to reduce these welfare losses using pricing instruments such as congestion tolls and parking fees. Studies that derive the welfare-maximizing design of such pricing instruments (for instance Arnott et al., 1991; Verhoef et al., 1995; Anderson and De Palma, 2004) generally conclude that they should be spatially differentiated and time-varying, as the externalities are heterogenous in space and time-of-day.

Only a limited number of empirical studies have been conducted on temporally and spatially varying price instruments in contrast to the wide body of theoretical work on the subject. There have been attempts to measure the behavioral reactions to differentiated pricing schemes using stated preference (SP) experiments (Azari et al., 2013; Albert and Mahalel, 2006), but with the usual caveat related to possible hypothetical biases (Fifer et al., 2014). Revealed preference (RP) experiments with differentiated road pricing schemes have for instance been conducted in Cambridge (Clarke et al., 1994) and Copenhagen (Nielsen and Sørensen, 2008), as well as, in the Netherlands (Knockaert et al., 2012; Peer et al., 2015). Based on these experiments' insights, our study tests a parking pricing pattern alike Arnott et al. (1991) proposal.

In this paper, we discuss the setup and outcomes of a five-week experiment in which parking prices were charged to commuters by deducting the applicable parking fees (in a price range of € 5 to € 25) from an initial virtual budget. The remainder of the budget was paid to the participants at the end of the experiment. The participants' travel behavior during the experiment was measured via a dedicated smart-phone app, automatically inferring and recording trips and travel modes based on state-of-the art pattern recognition techniques.

The paper is structured as follows. Section 2 discusses the experimental design. In Section 3 we explain the measurement of the behavior. Section 4 provides an overview of the participants and non-participants, inferring determinants of participation and drop-out behavior. Section 5 then discusses the main findings of the experiment, and Section 6 concludes.

2. Experimental design

2.1. Overview

We ran the field experiment to test how commuters react to spatially-differentiated and time-varying parking price policies. Participants were full-time workers living outside Vienna and commuting to Vienna by car each workday. They participated voluntarily. We offered monetary incentives to participants for changing their mode choice (away from car use) and morning parking time (away from their usual arrival time). Participants who started the experiment before 28 May 2018 (Group 1), earned up to € 175. Subjects who joined after that date received up to € 225 (Group 2).

The experiment lasted five weeks. In the first and last week of the experiment (which we refer to as pre- and post-measurement, respectively), we only monitored the behavior of the participants. During weeks 2-4, we exposed the participants to a virtual, personalized parking price scheme (see Section 2.2). Individuals received a virtual start budget before the experiment, from which the applicable daily parking charges were deducted. In case they did not change their behavior (away from the car and their usual arrival time) during these three weeks at all, the maximum parking charge applied each day, and the remaining budget equaled € 0 at the end of the experiment (no negative balance could occur). In the case of behavioral adaptations towards alternative modes and off-peak travel, the remaining budget (start budget minus parking fees) was transferred to the participants' bank account at the end of the experiment. Participants received no payout if the app measured less than three trips per week.

Participants earned up to € 25 extra by filling in stated preference questions[1] throughout the experiment (€ 1/question). Before the start of the experiment, participants had to fill in an initial survey with questions concerning their usual travel behavior (e.g., the usual arrival time at work), socio-economic characteristics, as well as attitudinal questions (based on Kroesen et al., 2017). Group 2 participants were additionally asked to fill in a questionnaire testing their understanding of the experiment. After analyzing the commuting behavior of Group 1 participants, we thought it is necessary to minimize the risk of participants not understanding the instructions. At the end of the experiment, participants were asked to fill in a questionnaire concerning the evaluation of the experiment and their own behavior. Finally, we used the Google cloud service "Routes" (Google, 2018) to infer door-to-door travel times.

2.2. Parking charges

The daily parking fees charged in week 2, 3, and 4 of the experiment varied by (i) week, (ii) parking location, and (iii) time-of-the-day. They only applied on workdays, and were determined based on the parking behavior detected by the app (see Section 3). The maximum daily parking fees for Group 1 participants amounted to € 5, € 10, and € 15, respectively. Charges for Group 2 participants were € 5, € 10, and € 25 (Group 2), respectively. Prices changed between weeks and not within. The order of occurrence of the three levels was randomized across participants to minimize the influence of seasonal or learning effects on our results.

The maximum daily fee applied if the participant was observed to park close to his/her workplace at his/her usual arrival time. Home and work locations as well as the typical arrival times were retrieved from the questionnaire. When a

[1] These are analyzed in a separate research effort.

participant used the car on a given day, she obtained discounts on the maximum daily charge by not parking close to work, and by parking earlier or later than the typical arrival time. In other words, parking fees decreased with spatial distance to work and temporal distance to the typical arrival time. The daily fee was € 0 if the participant did not park within a defined zone. The fee decreased linearly from the work-location to the zone border (spatial discount). The zone ended at the home location or 10 km from work if home and work location are more than 10 km apart. If the subjects parked before or after their typical arrival time they received a discount, which increased linearly with the temporal distance from the typical arrival time. It equalled 50% of the daily maximum fee at three hours before or three hours after the typical arrival time. Parking more than three hours before and three hours after the typical arrival time was free of charge. If the app did not record a trip from home to work on a given day, the maximum daily fee was charged. This penalty should prevent fraud (e.g., by turning off the phone).

Participants had to cover extra expenses that accrued due to changes in behavior (e.g. public transport tickets; park & ride fees). The net incentive was thus lower than the parking charges deducted from the initial budget. For instance, a weekly public transportation ticket from home to work costs between € 24.10 and € 63.00 (depending on the home location) for participants. A weekly ticket for public transportation in Vienna costs € 17.1. A weekly ticket for park and ride costs extra € 14.0 in Vienna, while it is free of charge outside Vienna. On average (see Table 1) participants pay € 39.0 for public transportation from their home district to Vienna (incl. travel in Vienna at a flat rate).

3. Measurement

The technology we used to measure the trips and modes is based on data collected by the participants' smartphones. Participants had to install a dedicated app (which was available for iOS and Android) that transfers acceleration and location data to a server, where trip stages and travel modes are automatically reconstructed. Trip reconstruction is based on machine learning algorithms published in Widhalm et al. (2012) and Nitsche et al. (2014), as well as multi-modal routing in a transport network graph (such as OpenStreetMap) to bridge GPS localization gaps.

Automatic trip reconstruction serves to determine whether, where and when a participant parks on a specific day. Our implementation is like a smartphone-based travel survey solution. Trip data are only transferred from the app to the server whenever the app detects the end of a trip.[2] The parking app solution therefore did not allow to communicate to the participants in real time whether

[2]Data transmission can be set to WiFi, to cellular network data transmission, or to both. For the experiment, the default data transmission was fixed to both. The participant could turn off cellular network data transmission.

a trip has been observed, and what trip characteristics (mode choice, timing, park location) were inferred. Upon every transmission, the smartphone sensor data were analyzed, and information was communicated to participants around 2 am each day. In case of missing data, the analysis was postponed to the following day.

The smartphone-based method for measuring the travel and parking behavior of participants has multiple advantages over GPS loggers placed in cars. Car-free trips such as public transport rides can be captured, which is essential for our research design. In addition, the initialization of the experiment is fairly straightforward and only involves the installation of an app on the smartphone. In contrast to smartphones, GPS logging devices (or Bluetooth beacons) would first have to be distributed to participants; then users would have to install them in their car and, in the case of Bluetooth beacons, connect them with their smartphones. After the end of the experiment, these devices might have to be returned to the organizers of the experiment. The efforts associated with this approach might lead to low participation and high dropout rates. The downsides of the smartphone-based approach include possible negative impact on the smartphone battery, transport mode mis-classifications and missing trips due to positioning problems, often related to the smartphone operating system. These downsides are discussed in Section 5.1 and Section 5.2 of the paper.

3.1. Commuting trip recognition

Clearly, an applicable parking fee can only be computed when a morning commute trip has been measured on a specific day. If no commute trip was measured, the participant paid the maximum parking fee for that day. The app may fail to measure a morning commute, if the smartphone location service was disabled, or GPS localization was poor.

3.2. Computation of applicable parking charges

Parking fees were derived by algorithms that identify the most likely parking location and parking time based on the sensor data transmitted by the app. The parking location is defined as the end of the last car trip that takes place as part of the morning commute. In the case there was no car trip within the morning commute (but a commute was measured), the parking location is assumed to be at home and the applicable parking fee is 0.

The parking location and time determined by the algorithms may not correspond to the actual location and time. Users could veto wrong transactions within the app. We have some knowledge on the performance of the underlying algorithms from Nitsche et al. (2014) who explain a structured testing of the mode detection algorithm used in our experiment.[3] It should, however,

[3]For a sample of 15 volunteers, they show that 67% of car trips were correctly classified. In 23% of the cases, the technology classified car trips as public transport (bus, subway or train) trip. Conversely, only 6% of train trips and just 2% of bus trips were wrongly classified as car trips.

be stressed that care must be taken when interpreting performance figures of travel mode identification systems in general due to the many possible factors that may have an influence, as well as the possible overfitting during training (Wang et al., 2018).

4. Participation

4.1. Recruitment

The experiment's target group is quite narrow: we recruited participants who commute from outside Vienna to Vienna. All invited participants drive (min.) five times per week to work, and park their car close to their workplace. All participants work full time, five days a week. Moreover, for them to participate in the study, they had to install the app, implying that they need to own a smartphone with an Android or iOS operating system.

The recruitment process included two main steps. First, we invited commuters to participate in a survey, announcing that some of them will be invited to participate in an experiment with monetary payouts, without mentioning what behaviors will lead to these payouts. This was done in order to reduce potential selection biases (see Section 4.3 for the corresponding discussion).

At the end of the survey, individuals who met the requirements for participating in the experiment (based on the self-reported information provided in the questionnaire), received an invitation to participate in the experiment. By 28 June 2018, 464 people were invited to the experiment, out of which 46.8% initially accepted the invitation to participate.

The recruitment has been challenging due to the highly specific characteristics of the target group, and the fact that the target group cannot be addressed via a single channel due to a lack of (formal or informal) organization among commuters. We thus employed multiple recruitment channels including (i) direct mailing, (ii) employers, (iii) recruitment partners, and (iv) others:

Direct mailing. 5000 pre-selected households within the suburbs of Vienna received an invitation to our experiment (without knowing whether the household includes individuals who are commuters). Three hundred of those filled in our questionnaire.

Employers. Letters were sent out to 1070 Viennese companies, asking them to support the experiment by informing their employees about it (in particular those from outside Vienna). Eight companies offered their support, among which two large public agencies. Those eight companies recruited in total ca. 1400 survey participants.

Recruitment partners. Three public organizations supported the recruitment. ÖAMTC, the main Austrian automobile association, sent newsletters to ca. 90,000 car owners in Eastern Austria, and the Austrian chamber of labor (Arbeiterkammer) sent a newsletter to ca. 1,600 commuters. A lobby organization for commuters (Pendlerinitiative) also sent out invitations to their members. The activities lead to ca. 450 survey participants.

Others. Other activities, such as Facebook advertisements, local billboards, newspaper articles in local news, and word-of-mouth lead to additionally ca. 130 survey participants.

Overall, a total number of 2776 individuals started the survey (84.1% completion rate), out of which 464 qualified as participants for the experiment based on the self-reported information provided in the questionnaire. Ultimately, 144 persons (30.8% of the 468) activated the app and started the experiment by 2 July 2018. 35 subjects (19.6%) successfully signed-up by 2 July 2018 but did not activate their user account on the app. 247 subjects (non-participants) actively indicated that they do not want to participate in the experiment. 18 initially accepted the invitation but did not provide an e-mail address. For 23 participants no suitable start date could be found, or they changed their mind. Only 1 subject indicated that he/she had no smartphone.

4.2. Participants' characteristics

In the second column of Table 1 we can see an overview of the main characteristics of the participants, mostly based on the initial questionnaire. For the questions concerning flexibility and attitude, participants could assign a maximum of 100 points, indicating very high flexibility in the former and high agreement with the proposed statements in the latter case.

60.4% of the participants self-report that they are more flexible in changing their schedule than their mode choice. 58% participants say they are not flexible in their mode choice (less than 20 out of 100 points). In contrast, only 21% state that they are not flexible in departing from home and 23% that they are not flexible in arrival time at work.

All participants reach the city center faster by car than by mass transit; however, most participants have a fairly good public transport connection. 77.1% of participants have a train station within 10 minutes driving distance. 45.8% lose less than 20 minutes door-to-door travel time when traveling by train. Car travel times are computed under uncongested conditions, while train travel times are estimated without waiting time at the station from which the train commute starts. Moreover, 73% of the participants prefer the car over the train for commuting purposes (giving overall more points to the car than to public transportation in the five Kroesen et al. (2017) attitude questions).

4.3. Selection effects

As participation is voluntary, self-selection effects may occur. We try to minimize them by not explicitly stating in the invitation to the experiment how monetary incentives can be earned, hence reducing the probability that persons who find it relatively easy to change their behavior sign up in disproportionate numbers. Clearly, dropout rates might then partially capture those participants who expect not be able to earn a sufficient amount of money at the end of the experiment to warrant the efforts of participating in the experiment. In Table 1 we see a comparison of key characteristics between non-participants (i.e., persons who filled in the initial survey and were invited to participate in the experiment but declined), participants (i.e., persons who activated the app), persons who dropped out prematurely (before 21 days), and full participants (i.e., those who completed more than 20 days out of 25 of the experiment). The first two and the last two groups are directly compared. The difference between the groups (Δ) and its significance is estimated by linear regression. We indicate missing data in brackets.

As expected we find that participants and non-participants do not vary significantly in most categories, with one exception. Younger participants seem to be significantly more willing to participate in the study. A possible reason is that they have a higher affinity for technology, in particular, smartphones (Pew Research Center, 2015; Google, 2016), and fewer privacy concerns (Olphert et al., 2005; Jiang et al., 2016; Ferreira et al., 2017).

Variables	Non-participants	Participants	Δ	Drop-outs	Full-participants	Δ
(Self-reported) Flexibility						
Mode choice (100 points = very flexible)	23	26	3	29	25	-4
Leave home (100 points = very flexible)	45	50	5	48	50	2
Arrive at work (100 points = very flexible)	47	53	6.	50	54	4
Attractiveness of train						
Driving time to closest train station [min]	8 [1]	8	-0	7	8	1
Car time vs. train time to the city center	1.7 [1]	1.7	0	1.8	1.6	0
Price for a weekly ticket to the city [€]	38 [9]	39 [3]	2	40 [2]	39 [1]	-0
Attitudes towards car usage						
Car (100 points = car, 0 points = public transport)	56	58	2	56	59	3
Socio-economic characteristics						
Male	55%	65%	10%.	53%	71%	17%*
Age	43	40	-3**	40	40	-1
Net-household income per year [€]	36,543 [72]	37,019 [40]	476	33,108 [12]	39,179 [28]	6,071*
Number of observations	247	144		49	95	
Significant coefficients are labeled as follows: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Table 1: Comparison between non-participants and participants, as well as, drop-outs and full participants

A substantial share of initial participants left the experiment prematurely, i.e. before the end of the 5-week duration. Among those 144 who activated the user account, 28% of Group 1, 44% of Group 2 dropped out before the post-measurement started. The significantly stronger drop-out rate of Group 2 manifests itself primarily in the first week. It might be the result of having (re-)invited members of Group 1 who did not activate their user accounts in the first round of the experiment. It is also plausible that Group 2 users were overwhelmed by the questionnaire testing their understanding of the experiment. Overall, only 95 subjects (52.2%) completed more than 20 out of 25 days (excl. the weekends) of the experiment. Slightly more participants filled in the post-questionnaire: 115 subjects (79.9%). Out of them, 91 are full participants.

Table 1 shows that more affluent participants and males are more willing to complete the experiment. We can only speculate, why this might be the case.

5. Analysis

In total, the app measured 1390 morning commuting trips (excl. holidays and weekends) from 95 full participants. Those participants traveled 85.1% of the distance per car, according to the records. The rest were walking and cycling trips (2.0%), motorbike trips (0.2%) and mass transit trips (12.9%; i.e., bus, train, tramway, and subway).

Missing trips and miss-classifications in the measurement may distort the results. We analyze them in the following two sub-sections. We then proceed with analyzing to which extent full participants adapted their behavior as anticipated (Section 5.3), and provide reasons why they did not adapt their behavior to a large extent (Section 5.4).

5.1. Missing trips

For full participants, the app measured a commute on 63.0% possible days (all workdays during the 5-week period times the number of active participants), i.e. 2,207 days. All participants had indicated in the questionnaire that they travel to work on all workdays.

The odds that the app measures a commute are relatively constant over the experiment. They do not significantly change between the treatments. There is some decline, however, over the course of the treatment phase: the percentage of measured commutes decreases from 65.2% in week 2 to 59.7% in week 4.

The number of measured commutes strongly deviates among full participants. For 20% each, the app recorded less than 47.1% or more than 81.8% commutes of all possible days.

5.2. Miss-classification

A large majority of participants are expected to park close to their workplace every day during the pre-measurement, given the information they provided in the initial questionnaire. However, we find that the algorithm inferred only for 87.1% of the 256 trips measured during pre-measurement that a full participant parked at work (i.e., not further than 1 km from work). In the remaining instances, the app identified the bus (6.3%), the car (0.4%), and public transport (6.3%) as the primary mode (the mode used for more than 50% of the distance of the morning commute).

Furthermore, users who objected to the observed measurements provided some insights (we ignored instances in which a veto concerned a trip for which no data has been recorded, since we have no possibility of verifying the information provided by the participant).[4] Overall, only few measurements were objected to, i.e., 34 trips out of 1390 trips taking place during weeks 2-4. Among those objections, we accepted 17 (50.0%): in 13 cases the parking location was wrongly detected (in all cases due to a false mode detection). In one case the parking

[4]Participants are likely to only veto against measurements if they are convinced that they suffer financial disadvantages due to the measurement.

time was wrongly detected, and in two cases the transaction was not recorded even though the app correctly measured the commuting trip. One veto was due to a communication issue.

5.3. Main results

We test for behavioral reactions for each of the 95 full participants. Two statistical tests (OLS regression) per participant reveal if she changed his/her behavior in the anticipated direction, i.e. whether she significantly increased the parking distance to work[5] (Test 1) and/or the parking time difference to their typical arrival time[6] (Test 2) with rising prices. The independent variables used in the two tests are the maximum applicable parking fee and a dummy for the post-measurement (in order to account for behavioral changes that carry over into the post-measurement). One observation is a subject's measured commute. Participants may be wrongly classified as mode detection is subject to error, as indicated by results of Section 5.2. Furthermore, we could not conduct a statistical test for 10 participants due to an exceptionally high number of missing trips (see Section 5.1). Participants who change behavior in the anticipated direction are referred to as adaptive.[7]

According to the statistical tests, we measure a significant behavioral change in the anticipated direction for 10 out of 95 full participants. 7 adaptives altered the location and 4 the time, 2 adjusted both. 9 out of 10 adaptives are part of Group 1 (13.6% of 66), and only 1 is part of Group 2 (3.4% of 29). A to us counter-intuitive result, as Group 2 participants received higher rewards than Group 1 participants. On the left of Figure 1 we can observe how parking location and time were affected by the monetary incentive among the group of adaptives. The behavioral change on the y-axis is 1 if users park outside the zone or more than 3 hours before/after their typical arrival time. It is 0 if participants park at work or at their usual arrival time. On average the Group 1 adaptives parked further away from work with increasing parking prices. Only at a price of € 15 they significantly changed their parking time. On the right of Figure 1 we can see how the mode share of the adaptives changed. The most used alternative was mass transit (i.e., bus, train, tram, and subway). However, some participants also switched to slow modes (bike) and the motorbike.

5.4. Potential reasons for lack in behavioral change

As shown in the previous section, only few participants changed their behavior during the treatment phase of the experiment relative to the pre-measurement.

[5] The parking location is truncated between 0 (i.e., park at work) and 1 (i.e., park at home or more than 10 km from work).

[6] The parking time is truncated between 0 (i.e., park at the typical arrival time) and 1 (i.e, park more or less than 3 hours before the usual arrival time). We exclude parking times outside the zone.

[7] In a handful of cases the behavior was significantly adjusted in a counter-intuitive direction: 2 participants parked closer to work, and 2 parked closer to their usual arrival time during the treatment phase compared to the pre-measurement.

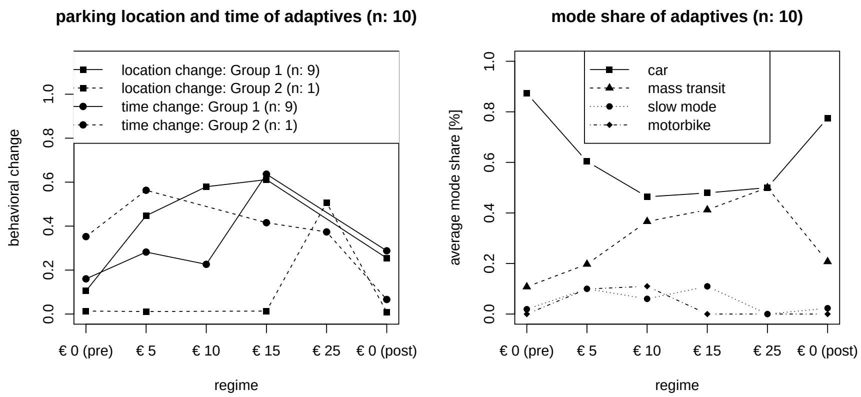

Figure 1: Parking location, time and mode share of adaptives during the experiment

There are multiple reasons for why participants might not have changed parking location and arrival time during the experiment despite the presence of monetary incentives (which were substantial in size during some of the treatment weeks, amounting up to € 25 per day). We discuss three main explanations: (i) experimental design (low (net) incentive, technical issues) (ii) lack of alternatives, and (iii) a lack of understanding the study and incentive structure. In the discussions we rely, among others, on the results of the post-questionnaire (see Table 2). For each question, they could assign a maximum of 100 points, indicating full agreement with the proposed statement. Using linear regressions, we test for differences between full participants (91 out of 95) and drop-outs (24 out of 49) (Δ_1), and adaptives (10 out of 10) and non-adaptives (81 out of 85) (Δ_2). The number of subjects not answering a specific questions is stated in brackets.

(i) Experimental design. The incentives (i.e. the parking charges) may not have been high enough. Most full participants indicated that the parking fees did not motivate them to change their behavior (Q24 full participants: 19.4) The implicit cost associated with the affirmed trouble of not using the car or arriving early or late at work, in particular, due to the extra costs associated with changing the mode towards public transport may have been higher than the parking charges. Stated preference questions, which are analyzed in a separate research effort, reveal that the average value of time of participants for commuting one hour by car is around € 17 and by public transportation significantly higher at € 24. Adaptives indicate that they were significantly more motivated to change their behavior due to the presence of the parking fees in the treatment period (Q24 Δ_2: 19.7*).

Overall, our experimental design and in particular the charges might have been too "implicit". The applicable monetary incentives were not as salient as in other experiments with a similar focus (e.g., Spitsmijden experiments conducted in the Netherlands (Knockaert et al., 2012; Peer et al., 2016)). Participants were informed about the maximum applicable fee. They knew about the computation of the charges due to the instructions provided to them. They could simulate the applicable charge on the app for a given time and parking location. However, the specific charges (for a given time and location) could not be communicated to the participants directly, due to the inherent spatial and temporal heterogeneity. The "implicitness" is also reflected in the fact that only the day after a given commute, participants received information on whether the trip has been recorded and what were the inferred trip characteristics. Finally, due to not all trips being registered (see Section 5.1), the expected monetary benefit from a change in behavior might have been down-scaled compared to a situation where all trips are recorded correctly. Indeed, the post-questionnaire provides evidence that some participants doubt if the app works well (Q25 full participants: 55.3). Indeed, adaptives show a significantly higher agreement with the statement that the app works well than non-adaptives (Q25 Δ_2: 42.9***).

Another reason for observing only small behavioral changes during the treatment phase relative to the pre-measurement might be that unlike costs in a real-life setting where the costs are deducted from the income and loss aversion might occur when costs are increased, participants of our experiment are likely to not face loss aversion, since the initial budget was only distributed virtually and the remaining budget was transferred to them only at the end of the experiment. Moreover, in a real-life setting with an actual cost increase, we would expect stronger behavioral adjustments due to an income effect, which again is not expected to be present in our setting as participants do not incur any overall income losses.

Finally, the focus of the experiment was fairly short-run. We expect fewer behavioral adjustments to be evident in a short-run setting compared to a long-run setting (i.e. a permanent price change with far-in-advance notification).

(ii) Lack of alternatives. The availability of substitutes might have been quite limited for our narrowly defined target group of car commuters with full-time jobs living outside of Vienna, but commuting to Vienna every day. If an alternative would be available, affordable and convenient, they would likely already use it. Most participants indicated that using alternative transportation modes take too long (Q2 full participants: 83.6) and is too cumbersome (Q3 full participants: 77.4). Furthermore, many subjects use their car after work for accessing recreational, shopping and social activities. Regarding arrival times at work, full participants seem to be a little more rigid in their departure time from home (Q12 full participants: 51.0) than in their start time at work (Q11 full participants: 41.8). Adaptives are more flexible in their start time at work than non-adaptives (Q11 $\Delta_2 : 34.0*$).

(iii) Lack of understanding. It might be that some participants did not understand the experimental setup and in particular the computation of parking charges (but note that even if they did not understand the underlying algorithms, they could have been able to identify the applicable charges for a given time-of-day and parking location). However, based on the evidence from our final questionnaire, this seems not to be the case for a majority of participants. Most participants stated that they knew how high the parking fees were (Q14 full participants: 75.9). Few participants indicate that they did not change the parking location (Q1 full participants: 15.6) or timing (Q10 full participants: 13.0) because they did not know that this will result in a discounted parking fee. In general, participants claim to have read the instructions very carefully (Q19 full participants: 85.9). Although some participants may have misunderstood the instructions, it would be plausible to assume that many of them dropped out prematurely due to their lack of understanding (and hence also did not fill in the post-questionnaire). Overall, adaptives participated more actively in the experiment (Q22 Δ_2: 13.0*). They informed themselves more often about the current parking fees (Q21 Δ_2: 22.4*) and reviewed their transactions more regularly (Q20 Δ_2: 17.6*) than non-participants.

6. Discussion and summary

In this paper, we discuss the results of an experiment in which commuters were offered monetary rewards for switching away from motorized transport, and changing their arrival time at work. We find that only a few participants adjusted their behavior, possibly due to the inconvenience related to changing one's schedule and mode of transport, as well as the amount that the participants would have to pay for using alternative means of transport, strongly decreasing the net incentive. Also the experimental design might have contributed to this result in multiple ways (as discussed in the previous section).

Our results are different from earlier, but related field experiments in transport, in the sense that we observe low adjustments in travel behavior despite the presence of substantial monetary incentives. This disparity can probably at least partially be explained by the fact that earlier field experiments have been subject to strong self-selection effects, which have been widely avoided here by not *ex ante* communicating to potential participants which behavioral adjustments would allow them to earn rewards.

Based on our findings, we can conclude that even very high monetary incentives (in the range of € 25 per workday) might not be sufficient to change people's behavior, at least in the short run and if alternatives tend to be widely inferior. In the light of this, the switch towards sustainable means of transport among commuters from suburban areas seems challenging, and pricing instruments seem to be insufficient (their sole introduction, without accompanying measures, would likely be associated with low levels of public acceptance). Complimentary measures such as investments in rendering public transport more comfortable (direct connections, etc.) seem to be necessary if a change in modal split should happen at a wider scale and pricing policies should be perceived as acceptable by the general public.

Funding

This work is part of the project "Innovative Policies for Sustainable Urban Transportation" (IP-SUNTAN), funded by the "ERA-NET Co-fund Smart

	full participants (n: 91)	drop-outs (n: 24)	Δ_1	adaptives (n: 10)	non-adaptives (n: 81)	Δ_2
Parking location: Why did you not (continuously) change your parking location on the way to your place of work despite parking fees in the experiment?						
Q1: I didn't know that I would get a discount on my parking fees if I parked my car far away from my workplace.	15.6 [5]	25.0 [2]	-9.4	1.1 [1]	17.3 [4]	-16.1
Q2: The travel time from my home to my place of work by alternative means of transport (e.g. public transport) is too long.	83.6 [2]	83.4 [1]	0.2	81.7 [0]	83.8 [2]	-2.1
Q3: The use of alternative means of transport (e.g. public transport) is too cumbersome.	77.4 [4]	80.6 [2]	-3.2	64.2 [0]	79.1 [4]	-14.9
Q4: I need my car for work (e.g. as a company car).	26.9 [6]	25.4 [2]	1.5	20.4 [1]	27.7 [5]	-7.3
Q5: I chauffeur children on their way to/ from work.	24.3 [3]	22.5 [2]	1.8	11.6 [1]	25.7 [2]	-14.2
Q6: I chauffeur adults on their way to/from work.	23.9 [6]	16.8 [4]	7.1	6.2 [1]	26.0 [5]	-19.8
Q7: I transport heavy goods that I need for my work.	8.5 [5]	1.4 [4]	7.1.	8.7 [1]	8.5 [4]	0.2
Q8: I transport heavy goods that I need before/ after work.	17.4 [8]	2.7 [5]	14.7*	6.9 [1]	18.7 [7]	-11.8
Q9: I use the car directly before/ after work for doing / shopping/ visits/ other activities.	85.2 [5]	82.9 [3]	2.3	76.8 [1]	86.2 [4]	2.3
Parking time: Why did you not (continuously) change your arrival time (at the parking place) on the way to your place of work despite parking fees in the experiment?						
Q10: I did not know that I would get a discount on my parking fees if I parked my car before / after my typical arrival time.	13.0 [5]	18.5 [2]	-5.5	1.4 [1]	14.3 [4]	-12.9
Q11: My work doesn't allow me to change my start of work.	41.8 [7]	54.1 [1]	-12.2	11.4 [1]	45.5 [6]	-34.0*
Q12: Private reasons do not allow me to change my departure time from home.	51 [6]	49.6 [4]	1.3	31.6 [0]	53.5 [6]	-21.9
Some questions about the experiment ...						
Q13: I knew how the parking fees were charged.	66.0 [0]	69.6 [1]	-3.7	78.3 [0]	64.4 [0]	13.9
Q14: I knew about the amount of parking fees charged.	75.9 [0]	74.2 [1]	1.7	91.8 [0]	74.0 [0]	17.8
Q15: I knew how much money I would receive at the end of the experiment.	44.1 [0]	48.3 [1]	-4.2	70.1 [0]	40.8 [0]	29.2*
Q16: I was aware that the parking fees increase with distance to the place of work.	56.9 [1]	57.7 [1]	-0.8	66.3 [0]	55.7 [1]	10.6
Q17: I was aware that parking fees are higher at certain times.	76.9 [1]	81.7 [1]	-4.8	94.1 [0]	74.7 [1]	19.4.
Q18: I was motivated to make money during the experiment.	47.3 [0]	50.2 [1]	-2.9	55.6 [0]	46.3 [0]	9.3
Q19: I read the instructions for the experiment carefully.	85.9 [0]	87.2 [0]	-1.3	94.0 [0]	84.9 [0]	9.1
Q20: I have regularly reviewed my transactions.	83.9 [0]	83.2 [1]	0.7	99.5 [0]	81.9 [0]	17.6*
Q21: I have informed myself about the current amount of parking fees.	70.2 [0]	66.0 [1]	4.2	90.2 [0]	67.8 [0]	22.4*
Q22: I have tried to actively participate in the experiment.	86.2 [0]	87.8 [1]	-1.6	97.8 [0]	84.8 [0]	13.0*
Q23: My parking fees were calculated correctly.	55.1 [0]	64.9 [1]	-9.8	46.6 [0]	56.1 [0]	-9.5
Q24: The parking fees have motivated me to change my behaviour.	19.4 [0]	37.9 [1]	-18.5**	37.0 [0]	17.2 [0]	19.7*
Q25: The app worked well.	55.3 [0]	31.4 [0]	7.8	69.5 [0]	23.6 [0]	42.9***
Q26: I used vetos for incorrectly charged parking fees.	31.4 [0]	23.6 [0]	7.8	69.5 [0]	26.6 [0]	42.8***

Significant coefficients are labeled as follows: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 2: Results of the post-questionnaire

Cities and Communities". Part of the work was carried out during Stephan Lehner's research stay at the University of California, Berkley, which was funded by a generous grant of the Austrian Marshall Plan Foundation.

References

Albert, G., Mahalel, D., 2006. Congestion tolls and parking fees: A comparison of the potential effect on travel behavior. Transport policy 13 (6), 496–502.

Anderson, S. P., De Palma, A., 2004. The economics of pricing parking. Journal of Urban Economics 55 (1), 1–20.

Arnott, R., De Palma, A., Lindsey, R., 1991. A temporal and spatial equilibrium analysis of commuter parking. Journal of public economics 45 (3), 301–335.

Azari, K. A., Arintono, S., Hamid, H., Rahmat, R. A. O., 2013. Modelling demand under parking and cordon pricing policy. Transport Policy 25, 1–9.

Clarke, D., Blythe, P., Thorpe, N., Rourke, A., 1994. Automatic debiting and electronic payment for transport - the ADEPT project: 3. Congestion metering: The cambridge trial. Traffic engineering & control 35 (4).

Ferreira, S. M., Sayago, S., Blat, J., 2017. Older peoples production and appropriation of digital videos: an ethnographic study. Behaviour & Information Technology 36 (6), 557–574.

Fifer, S., Rose, J., Greaves, S., 2014. Hypothetical bias in stated choice experiments: Is it a problem? and if so, how do we deal with it? Transportation research part A: policy and practice 61, 164–177.

Google, 2016. Share of smartphone users in Germany from 2012 to 2016, by age. Accessed: 2018-10-02.
URL https://www.statista.com/statistics/732504/germany-smartphone-users-by-age/

Google, 2018. Routes: Help your users find the best way to get from A to Z with comprehensive data and real-time traffic. Accessed: 2018-04-07.
URL cloud.google.com/maps-platform/routes/

Jiang, M., Tsai, H.-y. S., Cotten, S. R., Rifon, N. J., LaRose, R., Alhabash, S., 2016. Generational differences in online safety perceptions, knowledge, and practices. Educational Gerontology 42 (9), 621–634.

Knockaert, J., Tseng, Y.-Y., Verhoef, E. T., Rouwendal, J., 2012. The Spitsmijden experiment: a reward to battle congestion. Transport Policy 24, 260–272.

Kroesen, M., Handy, S., Chorus, C., 2017. Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. Transportation Research Part A: Policy and Practice 101, 190–202.

Nielsen, O. A., Sørensen, M. V., 2008. The AKTA road pricing experiment in Copenhagen. Road pricing, the economy and the environment, 93–109.

Nitsche, P., Widhalm, P., Breuss, S., Brändle, N., Maurer, P., 2014. Supporting large-scale travel surveys with smartphones - a practical approach. Transportation Research Part C: Emerging Technologies 43, 212–221.

Olphert, C., Damodaran, L., May, A., 2005. Towards digital inclusion - engaging older people in the digital world. In: Accessible design in the digital world conference. Vol. 2.

Peer, S., Knockaert, J., Verhoef, E. T., 2016. Train commuters scheduling preferences: evidence from a large-scale peak avoidance experiment. Transportation Research Part B: Methodological 83, 314–333.

Peer, S., Verhoef, E., Knockaert, J., Koster, P., Tseng, Y.-Y., 2015. Long-run versus short-run perspectives on consumer scheduling: evidence from a revealed-preference experiment among peak-hour road commuters. International Economic Review 56 (1), 303–323.

Pew Research Center, 2015. Is your cellphone a smartphone, such as an iPhone, a Blackberry or the like?*. Accessed: 2018-10-02.
URL https://www.statista.com/statistics/539409/smartphone-ownership-by-age-in-selected-countries/

TOMTOM, 2017. Tomtom traffic index: Measuring congestion worldwide. Accessed: 2017-05-22.
URL tomtom.com/en_gb/trafficindex

Verhoef, E., Nijkamp, P., Rietveld, P., 1995. The economics of regulatory parking policies: the (im) possibilities of parking policies in traffic regulation. Transportation Research Part A: Policy and Practice 29 (2), 141–156.

Wang, L., Gjoreski, H., Murao, K., Okita, T., Roggen, D., 2018. Summary of the Sussex-Huawei Locomotion-Transportation Recognition Challenge. In: Proceedings 6th International Workshop on Human Activity Sensing Corpus and Applications (HASCA2018),. ACM, pp. 1521–1528.

Widhalm, P., Nitsche, P., Brändle, N., 2012. Transport mode detection with realistic smartphone sensor data. In: Pattern Recognition (ICPR), 2012 21st International Conference on. IEEE, pp. 573–576.