Center for European, Governance and Economic Development Research

cege

Discussion Papers

Number 394 – June 2020

THE EFFECTS OF FINANCIAL AND NON-FINANCIAL INCENTIVES ON THE DEMAND FOR A SUSTAINABLE DRT SYSTEM

Aljoscha Minnich
Holger A. Rau
Jan Schlüter

Georg-August-Universität Göttingen

ISSN: 1439-2305

The Effects of Financial and Non-Financial Incentives on the Demand for a Sustainable DRT System

Aljoscha Minnich*[1, 3], Holger A. Rau†[2], and Jan Schlüter‡[3]

[1]Center for Earth System Research and Sustainability (CEN), University of Hamburg
[2]University of Göttingen
[3]Max Planck Institute for Dynamics and Self-Organization

June 2020

Abstract

This paper analyzes in a large-scale field experiment (N = 2,980) the incentive effects of monetary vs. non-monetary incentives on the usage of a sustainable Demand Responsive Transport (DRT) system. Financial incentives were implemented by offering customers vouchers, which were received when they reached a certain threshold of rides with the DRT service (EcoBus). In the non-financial incentive treatment, we applied the same thresholds. In this case, we exploited the sustainable character of the EcoBus and offered environmental certificates which documented the saved level of carbon dioxide because of the bus usage. The data show strong support that financial incentives excellently work to increase the demand for a sustainable transport service. EcoBus rides nearly doubled during the intervention phase. Interestingly, non-financial incentives also have a positive effect on the demand for the bus service. However, the effect is attenuated at the end of the treatment phase. Thus, financial incentives outperform non-financial incentives.

JEL Classification numbers: C93, D12, D83, D91.
Keywords: Demand Responsive Transport, Field Experiment, Incentive Effects.

*Grindelberg 5, 20144, Hamburg (Germany), *E-mail: aljoscha.minnich@uni-hamburg.de*

†Corresponding author, Platz der Göttinger Sieben 3, 37073 Göttingen (Germany), *E-mail: holger.rau@uni-goettingen.de*

‡Am Faßberg 17, 37077 Göttingen (Germany), *E-mail: jan.schlueter@ds.mpg.de*

1 Introduction

In recent years, sustainable development in ecological, economic, and social terms has become increasingly important. Empirical evidence suggests that the European Union (EU) is one of the largest greenhouse gas emitters (González et al., 2014a; 2014b). As a consequence, the EU committed itself to ambitious climate goals in the Paris agreement of October 5, 2016, which implied the reduction of greenhouse gas emissions by the year 2020 (Liobikienė and Butkus, 2017). In the EU, an important domain of greenhouse gas emissions is the transport sector, as it amounted to 20.8% of overall greenhouse gas emissions in 2014. More precisely, it is the second-largest source of emissions after the energy sector (Andrés and Padilla, 2018). Thus, it is meaningful to focus on strategies which stimulate the reduction of greenhouse gas emissions in this sector. In this respect, local public transportation is an interesting domain, as there is potential to increase the efficiency and demand for these services. For example, Germany, a major player in the EU, invested approximately 130 million Euros over two years to improve the air quality by supporting projects of local public transport authorities in five model cities (see Federal Environment Ministry of Germany, 2018). Besides a higher supply, improved routing and new bike paths, monetary incentives are used to reduce nitrogen dioxide pollution. However, a key problem of local public transportation is the lack of supply in rural areas. Velaga et al. (2012) argue that the distribution of dwellers over large areas, the low population density, and the unpredictable level of demand cause the transport problems in rural areas.

Thus, demand responsive transportation (DRT) systems may be an interesting approach to increase the demand for public transportation in rural areas. The system is an intermediate form of public transportation, where the service is run by small buses with variable routes which are determined by the demand of the passengers (Brake et al., 2004). In principal, a DRT system can be more cost effective and flexible for rural areas than standard public transportation services. Nevertheless, many of them have failed because the DRT operations used were not realistically costed (Davison et al., 2012) and had problems in the marketing of these services (Enoch et al., 2006).

In this paper, we focus on the second aspect, i.e., we study ways to increase customers' acceptance of a DRT service. Therefore, we conduct a natural field experiment with a DRT system in a rural area in Germany. In the field experiment we analyze the effects of financial and non-financial incentives to increase the demand for DRT. Applying extrinsic incentives to stimulate DRT systems is motivated by an example in which financial rewards were applied to urban public transportation systems. That is, in 2017 the city of Bologna (Italy) used the mobile application "Bella Mossa" to introduce financial incentives to stimulate the travel behavior of customers. A crucial difference to our study is that the project does not aim at the efficiency of a specific mode of transport, such as a DRT service. Instead, the goal was to guide car users toward a more sustainable behavior

(Martyn-Hemphill and Kelly, 2018). Users of the app were promised financial rewards, such as free beer, ice cream, or cinema tickets, if they refrained from driving and instead used public transport, walked or cycled. The app also displayed the saved amount of carbon dioxide. Bowden and Hellen (2019) report positive effects of the Bella-Mossa project, i.e., about half of everyday car users showed some form of sustained commitment and behavioral change. Although, the net effect of the project seems to be positive, it is unclear whether the implementation of financial incentives had some negative side effects. The psychological literature on incentives highlights that financial incentives sometimes have the potential to crowd out subjects' intrinsic motivation (Gneezy et al., 2011). The literature on motivational crowding out finds that financial incentives may especially backfire in contexts where intrinsic motives play a key role. Examples range from negative consequences on people's willingness to donate blood (Titmuss, 1970; Mellström and Johanession, 2008), or on subjects' performance when working as fundraisers (Gneezy and Rustichini, 2000). Financial incentives may also have the potential to blow out subjects' intrinsic motivation to protect the environment. In a survey, Frey and Oberholzer-Gee (1997) show that participants were less willing to accept the building of a power plant in their neighborhood when offered financial incentives. On the other hand, in the domain of habit formation financial incentives have been proven to have positive effects. Charness and Gneezy (2009) find that people increase their gym attendances when paid to do so. There is evidence that people reduce smoking when financially rewarded (e.g., Gneezy et al., 2011). Habit formation is also related to transportation behavior. People may find it more comfortable to use their cars, although they know that using the bus would have a positive effect on the environment. In this respect, gifting free bus tickets may affect their habits, i.e., trying out this service may convince them to switch to buses (Fujii and Kitamura, 2003).

To test incentive effects, we analyze a situation where we pay citizens for using an environmentally-friendly mode of transportation. In this respect, we can test how well financial and non-financial incentives work when subjects may be intrinsically motivated. Do financial rewards for a DRT service have similar positive effects as in habit formation? Or is it that they are discarded, when customers are intrinsically-motivated and paid for doing something good. It will also be interesting to test whether non-monetary rewards in the form of environmental certificates positively affect the demand for the DRT service. This is also important from the perspective of efficiency considerations, as these measures come at nearly zero cost. To test these effects, we ran a natural field experiment between August 13, 2018, and February 24, 2019. The field experiment was conducted in connection with the "EcoBus" project. The EcoBus is a door-to-door DRT system that was installed for a trial period of six months in a rural area in northern Germany called Harz. The system was fully integrated in the public transport. Its main aim was to reduce environmental and personal costs in comparison to motorized private transport. This is achieved by applying ride-pooling. The project was initiated by the *Max Planck Institute* *for Dynamics and Self-Organization* in Göttingen (Germany) and regional transportation authorities.

Our study contributes to the literature in several ways. In contrast to Bowden and Hellen (2019), we focus on a DRT system and try to demonstrate effective ways to increase the acceptance of this mode of transport. By contrast, in their setting, customers compete against each other and receive financial rewards if they substitute daily car usage with different services (e.g., walking, cycling, bus)(see Martyn-Hemphill and Kelly, 2018). We have two clear-cut treatments which differ in the incentives (financial incentives vs. no-financial incentives) and reward customers if they achieve the same performance in each testing condition.[1] In addition, we apply a quasi-experimental evaluation in comparison to self-disclosures on the car use of everyday car drivers. The framework for testing the effectiveness of incentives is particularly suitable here, as our experiment is conducted in the pilot phase of the bus, where customers could not form good or bad long-term experiences with the service. Moreover, our analysis can help to shed some light on the overall effectiveness of rewards in the context of DRT and stimulate discussion on particularly appropriate rewards for future gamification approaches (see Yen et al., 2019).

Our main research question is whether financial and non-financial incentives help to increase sustainable transport behavior (cf. Chapman, 2007). Specifically, we test this potential effect in the form of an increased demand for EcoBus rides, by applying a difference-in-differences (DiD) approach. After a trial phase without any incentives we implemented either the financial/non-financial or no incentives. In the DiD approach we compare the difference in the change of the EcoBus demand between the incentive treatments and the no-incentive treatment. Financial incentives were implemented in the form of vouchers from local firms, whereas we used environmental certificates, displaying information of the abated carbon dioxide as non-monetary incentives.

We find that financial incentives significantly increased the demand for the DRT service, which nearly doubled during the intervention phase. Interestingly, the data show that even non-monetary incentives stimulate the demand for DRT. However, we find evidence that in the late periods non-monetary incentives had some negative effects and lowered the demand for DRT. We speculate that this may indicate potential motivational crowding out, as customers in the environmentally-framed non-incentives treatment may have grown disappointed when realizing that the pilot would soon stop. By contrast, we find that the positive effects of financial incentives are durable and therefore outperform non-financial incentives.

[1] Bowden and Hellen (2019) also report descriptive statistics, showing evidence that Gamification may have positive effects for sustainable behavior. However, it is hard to compare the direct effects of financial vs. non-financial incentives, as their study design does not include a non-financial incentives treatment which can be compared to the financial incentives system.

2 Study Data

This section gives an overview of our field setting and the data used for the analysis. First, the DRT system EcoBus and the corresponding customer data collection are presented. Secondly, the accompanying survey is described. Finally, the characteristics of the region are presented briefly to provide more background information.

2.1 The EcoBus pilot project

The EcoBus is a DRT system that offered door-to-door rides in the region of Oberharz in Germany.[2] During the first pilot phase there was no incentive scheme implemented, as the aim was to measure customers' general preference for the DRT service. The second trial period took place from August 11, 2018, to February 28, 2019. Customers could book their rides via telephone, phone app or website. The maximum number of bookable seats was eight, due to the capacity of each bus. It was possible to use the EcoBus at the same price levels as the local transport, and the different types of tickets were available on the bus itself or at booking offices. The operating time was from 6 a.m. to 10 p.m. on weekdays, with modified times during the weekends.[3] The goal of the EcoBus project was to analyze the demand of a DRT service for people in rural areas. The project tested their acceptance of this new type of transport as an alternative to private cars, since mobility in rural areas typically depends on private cars. The project was initiated by the *Max Planck Institute for Dynamics and Self-Organization* in cooperation with the local public transport associations *Regionalverband Großraum Braunschweig* and *Zweckverband Verkehrsverbund Süd-Niedersachsen*. It was financially supported by the *Südniedersachsenprogramm* and the *European Regional Development Fund*.

The data encompass recordings from the EcoBus customer accounts. Every booking request was registered in the middleware of the project. Since customers using a traditional telephone could not be allocated to an account, only the travel patterns of passengers using the website, Android- or iOS applications could be observed. All successful bookings were aggregated on a weekly basis for every customer account. Besides, the registration date and information about the number of additional persons on the bus during a ride, the driving and waiting time, and the number of cancellations were compiled per week. This was divided by the weekly bookings based on the data collection of the middleware. All in all, 38,472 successful bookings were processed. The bookings referred to the transportation of 51,678 passengers.[4] During the time of the experiment, there was a change

[2] The service area of the second pilot project can be found in Appendix A. It can be divided into two parts, namely a full-service area in the major part of the service area and a booking constraint area in the north so that there is no competition with the local transport in the rather urban area.

[3] On Fridays the bus ran between 6 a.m. and 2 a.m. of the next day. On Saturday it ran between 8 a.m. and 2 a.m. of the next day. On Sunday the service ran from 8 a.m. to 10 p.m.

[4] However, the total demand could not be met, due to a mostly busy system, resulting from the large operating area and the fact that the algorithm was not able to induce ride-pooling in many cases because of a rather inflexible route plan.

concerning the lead time of the EcoBus booking. This might have led to small changes in travel behavior. In the beginning, it was possible to book journeys in advance on the same day. However, from December 10, 2018, the lead time was reduced to booking an hour in advance of the time of departure. For example, before the change, it was possible to make a booking at 8 a.m. for a trip at 5 p.m. After the change the pre-order for the trip at 5 p.m. could only be done starting from 4 p.m. In our analyses we apply DiD regressions with 27 time dummies, which account for the possible effects of this change.

2.2 The Region

The service area is located in the "Oberharz region" of the German federate state Lower Saxony (see Percy, 1872, p.248). The main share of the state can be characterized as a rural area (see Federal Institute for Research on Building, Urban Affairs and Spatial Development, 2017). Apart from four larger towns (Goslar, Langelsheim, Clausthal-Zellerfeld and Osterode), the rural structures also apply to the service area.

In the service area, there are approximately 82,000 inhabitants.[5] As the region has a hilly landscape, it serves as a tourism area during the whole year (see State Office for Statistics Lower Saxony, 2019b). Furthermore, it is a former mining area, which is located next to the bygone border between East and West Germany. The population trend and the forecasts of the region outline that the population is aging and declining (see State Office for Statistics Lower Saxony, 2019a). The average disposable per capita income per year is 20,269 in Goslar and is thus lower than the average in the state of Lower Saxony (21,045) and Germany (21,952) (see Baumann and Seils, 2019). The public transport supply in the Oberharz is not highly developed, especially outside of school hours.[6] Due to the hilly landscape, the inflexible and time-consuming public transport, besides using private cars there is no real means of transport. Thus, the EcoBus may be an appropriate service to test whether DRT can support the existing public transport structure to increase the flexibility and operating hours (see also Berg and Ihlström, 2019).

2.3 Survey data

An accompanying survey was conducted before we introduced the financial and non-financial incentives. The aim of the survey was to learn about customers' perception and motivation to use the EcoBus.[7] The survey was implemented between October 10 and November 19, 2018. It focused on travel behavior, personal environment, motivation, and demographic information of the participants (see Appendix B for further details). Overall,

[5] Derived by own calculations based on the local authority Braunlage 2018, local authority Goslar 2017, and the local authority Osterode 2012.

[6] Own assessment based on local transport authority RBB n.y., local transport authority VSN n.y.

[7] The data was also used in another study (Nyga et al., 2020), which analyzed the effects of susceptibility, eco-friendliness and dependence on the consumer's willingness-to-pay for the EcoBus.

194 questionnaires were filled out properly. The questionnaire included a maximum of 38 questions with an estimated completion time of 10 minutes. It was possible to access the questionnaire via a notification on the EcoBus website or mobile application, where either a mobile or web version was displayed. All EcoBus users had access to it. Five Amazon vouchers with a value of 10 Euros were used as a possible reward for participation. It was possible to state the email address at the end of the survey to participate in the lottery and to get information about the survey results. We implemented the treatment phase (on the introduction of financial and non-financial incentives in the EcoBus service) on the last day when the questionnaire was processed.

3 Experimental design

Our field experiment is designed to analyze the effect of financial and non-financial incentive schemes on the demand for a DRT system. An interesting feature of this experiment is that it aims to increase the demand for a special transport service (DRT) which, for environmental reasons, is of importance for rural areas. Note that so far these services have mostly failed in terms of achieving a high demand. This section provides information about the incentive types used, the temporal and spatial implementation of the experiment, and the treatments.

3.1 Types of Incentives

We study the effects of financial and non-financial incentive schemes on the demand for EcoBus rides. We implement the financial incentives in the form of vouchers for offers of local leisure activities, whereas we apply environmental certificates as non-financial incentives. The incentive schemes are randomly assigned to customer accounts, based on their postcode (Appendix C.1 shows examples of the implementation). As a benchmark scenario, we use a setting where customers did not receive incentives at any time. The general structure to gain financial and non-financial incentives is the same in both incentive treatments. It works as follows.

When customers complete an EcoBus booking, the system allocates a virtual collective stamp to the customer account. Customers receive a collective stamp for each ride. Once they reach a certain threshold of collective stamps, they qualify for a bonus level. The lower level ("silver bonus") is reached after they achieve 10 collective stamps, whereas the higher level ("gold bonus") is awarded to users after they collect 20 stamps. Subjects were informed by the app that this only worked if they booked via the website or phone app. Moreover, they were informed that only bookings in the period between November 19, 2018, and February 28, 2019 (our treatment period), would be considered. The EcoBus website and the app included a menu item called "bonus program." The main menu of the bonus program displayed the number of collective stamps of the customers, an overview of the incentives (financial or non-financial), and the possibility to request that the incentive be sent to the connected mail account.[8] The customers received a notification at the beginning of the bonus program and when they managed to reach the thresholds. In addition, the news section of the EcoBus included information about the implementation of the bonus program.[9]

In the financial-incentives treatment subjects could exchange their collective stamps for vouchers. More precisely, they could choose between three vouchers from recreational facilities with different offerings for the silver and golden bonus levels. The cooperation partners were located in the service area of the EcoBus. The company “GlowGolf Harz” offered a voucher for anaglyph 3D glasses in exchange for the silver bonus. The glasses could be used with their offer of a special minigolf game. For the gold bonus they offered a free game for a second person who accompanied the customer. The number of their vouchers was unlimited and they were valid until the end of the year 2019. “Erlebnis-BocksBerg” offered either a round trip via a gondola for the silver level or a round trip and a coffee and pie menu for the golden level. The same conditions for availability and duration of the voucher program applied. Aloha Aqualand offered for a silver bonus access to a sauna and a swimming area for two hours. Whereas, the access was granted for a whole day when customers exchanged a gold bonus. Both bonus levels were only valid for the second person if the first person was a regular paying customer. Aloha Aqualand provided 500 vouchers in total, and the validity ended on September 30, 2019.[10]

The non-financial incentive was an environmental certificate that gave information to the subjects on the amount of saved CO_2 with a ride-pooling factor of 1.56 persons on average, in comparison to the usage of a car. The document included an environmental design, which displayed either a silver or a golden coin to reflect the bonus level. Importantly, as mentioned above, we kept constant the general incentive structure. That is, in the non-financial incentive treatment customers knew that they would be awarded collective stamps for each EcoBus ride. They also knew that they could achieve a silver bonus level (when 10 collective stamps were achieved), or a golden bonus level (with 20 collective stamps). In the non-financial incentives treatment they were told that they could exchange the stamps for “silver environmenal certificates” or “gold environmental certificates,” if they reached the corresponding threshold. On the certificates of the silver and the gold levels, we depicted either 10 or 20 coins on the letterhead. Moreover, the certificates gave information on the amount of saved CO_2 for the two threshold levels respectively. There was no limit to the supply of certificates, since they were distributed online. Appendix C.2

[8]Furthermore, customers were told that the bonus could only be requested as long as the incentives were available in order to address possible supply shortages of the incentives in advance.

[9]The news was that there was a silver and gold bonus available with the help of collective stamps and where the new bonus program could be found in the individual applications.

[10]We are aware of the fact that the three financial incentives may not be perfectly comparable. However, this should not affect the results of the comparison of financial vs. non-financial incentives, as subjects in the financial treatment could choose between the three types of incentives. Importantly, we do not apply the different types of financial incentives in our treatment comparisons.

gives an overview of the incentives, the validity, and the supply of the different schemes.

3.2 Temporal and Spatial Implementation of Incentives

In all treatments the travel pattern was initially observed for 14 weeks without any intervention, and then the incentive scheme was introduced for another 14 weeks. The first two and the last four days were not taken into account in the analysis due to an incomplete week in each case. The spatial implementation was designed in such a way that it was less likely people could find out that there existed different incentive types and would feel unfairly treated. To ensure this, EcoBus customers were asked to declare their corresponding postcode voluntarily in the registration process of the website or app account. Overall, the objective was to achieve an equal distribution of accounts for the incentive types so that the full service and the booking constraint area were equally distributed as well (see Appendix D). Each group of postcodes was randomly assigned to an incentive scheme.[11] The results of the allocation are shown in Appendix D. The idea was that for the areas of financial and non-financial incentives, some EcoBus customers should not be given incentives at all. However, because of a technical problem, the postcode-treatment allocation only assigned the financial and non-financial incentive treatments to the customers. Therefore, we exploit another group as a benchmark, which was not selected based on the postcode, but nevertheless did not receive any incentives. This was possible as the system by default did not allocate incentives to the customers whenever something went wrong with the registration in the app. This happened when customers did not enter their postcode in the EcoBus app. In that case, the postcode of the starting point of the first ride in the treatment phase was used to allocate the incentives. They were then asked to log in again to the system. If they failed to do so, the system allocated by default no incentives to them.[12]

4 Related Literature and Hypotheses

In this section we summarize the related literature and state our hypotheses. In our design, we implement the financial and non-financial incentives by applying a smart-phone

[11] The service area was divided into two areas with different booking rules (light green and dark green) as shown in Appendix A. In the dark green part of the service area there were no booking restrictions and customers were free to choose the start and end point of their EcoBus journey. In the other part this was not possible in order to avoid competition for the local bus authority. So if the starting point of the EcoBus trip was in the light green area, the trip could not end in the light green area, but only in the dark green area to avoid the same route coverage of the EcoBus and the local bus authority. The postcodes do not give an exact display of the different types of service area.

[12] If they logged in, the postcode matching algorithm either matched them to the financial or non-financial treatment, based on the postcode where their first ride started. Another possibility for why no incentives were allocated to customers, was that they entered a Claustahl postcode and did not re-login after the first ride. We wanted to have all treatments run in Clausthal because this region is large and attractive. To ensure this with our system, these customers also had to re-login.

app and a website app. The design of the app shares similar elements as in recent pilot studies, which experienced positive effects, by using game elements ("gamification") in combination with financial incentives to promote sustainable transport (see Anagnostopoulou et al., 2016, for a literature review). Although most of these papers lack power, they suggest that gamification elements may help to increase sustainable behavior (Buningh et al., 2014; Bowden and Hellen, 2019). In this paper, we use our app to test the effectiveness of financial and non-financial incentives to increase the demand for a DRT service.

Regarding the motivational effects of financial incentives, several survey studies highlight a conflict between the direct extrinsic effect and the effects on intrinsic motivation in the short and long run (Gneezy et al., 2011; Bowles and Polania-Reyes, 2012; Festré and Garrouste, 2015; Bolderdijk and Steg, 2015). That is, financial incentives may have negative effects on social norms, image concerns or trust (Gneezy et al., 2011). Moreover, evidence from matching donations suggests that incentives may have negative effects in the long-run (e.g., Meier, 2007). Nevertheless, incentives can be a cost-effective option, as their success seems to depend on the design or the type (monetary or non-monetary) of incentives (Gneezy et al., 2011; Bowles and Polania-Reyes, 2012). To avoid crowding-out effects it is important to choose an appropriate level of compensation, which is neither too low nor too high (Gneezy and Rustichini, 2000; Ariely et al., 2009; Gneezy and Rey-Biel, 2014). Furthermore, a possible solution to avoid a crowding-out effect might be the provision of small or large gifts, without mentioning the price (Ariely, 2008; Falk, 2007; Maréchal and Thöni, 2018). Gift cards or vouchers are other examples which can have a positive impact when used as incentives (Lacetera and Macis, 2010; Bareket-Bojmel et al., 2017; Lacetera et al., 2012).

We follow this approach to avoid motivational crowding-out effects in the presence of extrinsic incentives. That is, our app playfully introduces financial incentives in the form of vouchers for gifts, which do not have a low financial value. We expect that this will have a positive effect on the demand of our DRT service (EcoBus). This is also motivated by the positive evidence of financial incentives of appropriate size in the domain of habit formation. For instance, Charness and Gneezy (2009) show that people increase their gym attendances when paid for it. Similar effects on financial incentives are reported in the field of transport, where several studies find that subjects increased the usage of public transportation after they received free tickets (Hunecke et al., 2001; Fujii and Kitamura, 2003; Bamberg, 2006; Thøgersen and Møller, 2008). Thus, we derive our first hypothesis on financial incentives.

Hypothesis 1: The financial incentives increase the demand for EcoBus rides.

Turning to non-financial incentives, there is evidence that non-price information strategies can help to motivate conservation behavior.[13] In studies on private energy consumption Allcott and Rogers (2014) and Asension and Delmas (2015) find that informing households with non-price information strategies on the positive effects of energy conservation helps to reduce energy consumption. Non-financial incentives may also work in the field of transport, i.e., Graham et al. (2011) show that college students who reported their daily-car use on the internet, significantly reduced car driving when they received feedback on the saved gas costs and on the abated carbon dioxide. Our non-monetary incentives treatment shares similar characteristics to non-price information strategies. That is, EcoBus users receive information about the abated carbon-dioxide emissions as a direct consequence of their rides. Thus, it is likely that the environmental certificates serve as signaling devices, providing the information that sustainable personal travel patterns have a positive impact on the environment. Therefore, we expect that the non-financial incentives will increase the EcoBus usage. This leads to Hypothesis 2.

Hypothesis 2: The non-financial incentives increase the demand for the EcoBus.

As compared to non-monetary incentives, financial incentives have proven to be more durable, i.e., they are more likely to work in later time periods. It is conceivable that customers will tend to be more motivated to reach the thresholds of financial incentives and that this will be particularly the case at the end of the pilot phase (Ito et al., 2015; Masclet et al., 2003; Dolan and Metcalfe, 2015). Therefore, we overall expect that financial incentives are more effective than non-financial incentives.

Hypothesis 3: The financial incentives have a stronger effect on the demand for the EcoBus than the non-financial incentives.

5 Results

The analysis regarding the EcoBus travel behavior includes all accounts which completed at least one ride and where we have information on the corresponding postcode.[14] Overall, the data consist of 1,012 accounts with financial incentives, 413 accounts with non-financial incentives and 1,555 accounts without any incentive.

Section 5.1 gives a short overview of the travel behavior of EcoBus customers. Afterward, we present our main results in Section 5.2 and Section 5.3, which focus on *Difference-in-Differences* (DiD) analyses to figure out whether financial and non-financial incentives stimulate the demand for the EcoBus service. In Section 5.4 we conclude the results section with robustness checks.

[13]In the field of organizational economics, it was also shown that non-financial incentives in the form of symbolic rewards have a positive effect on the performance of workers (Kosfeld and Neckermann, 2011).

[14]One account is not considered because the incentive type was wrongly allocated.

5.1 Travel Pattern

We first overview the travel pattern before and after the treatment phase. To compare the effect of financial incentives to the benchmark group, we applied “coarsened exact matching.” We opt for this approach, as it is suitable for different variable types and for large data sets (see King and Nielsen, 2019). We believe it is important to use a matching approach when comparing the incentive data to the benchmark treatment. The reason is that the customers in the incentive groups may be different from the customers in the no-incentive group. The reason is that in these cases something went wrong with the registration, i.e., customers in the no-incentive group may be subjects who did not want to provide their postcode voluntarily. Another reason is that those subjects just simply did not manage to re-login. The coarsened exact matching mechanism controls for individual heterogeneity and matches subjects based on their similarity. Thus, the matching approach allows us to explain causal effects in the comparison of the two groups. More precisely, we first used the automatic mode and independently matched the incentive types to the control group, based on the similarity of aggregated weekly trips in the pre-treatment phase. To generate figures 1 and 2, the weekly trips were multiplied by the weight of the coarsened exact matching (at a weight of 0 the observations were removed). We start with the analysis of the effect of financial incentives on the demand for the EcoBus (Hypothesis 1). Figure 1 shows the actual weekly travel behavior indicating the means of *weekly EcoBus journeys* of the financial incentive group (red line) and the corresponding control group without incentives (black line), which resulted from the matching approach with the financial-incentive treatment. The white background indicates the pre-treatment phase (week 1–14), whereas the blue background indicates the treatment phase for the financial incentives (week 15–28). In the right panel of the diagram, we present bar charts, which focus on the average journey per EcoBus account before and after the treatment phase. Again, the red bars focus on the financial-incentives treatment, whereas the black bars focus on the control treatment.

The time lines show that before the treatment phase, customers in both treatments slightly increase the demand over time. The trend is almost parallel, which shows that subjects in the control treatment apparently do not differ from customers in the financial incentives treatment. The only exception appears at the end of the pre-treatment (weeks 13–14), where the trends become different. For this reason, we also test our main effects by running DiD regressions with controls, which focus on the differences in the increase of the demand of incentives and non-incentives, when comparing the pre-treatment phase and the treatment phase. In our diagram, we find in the treatment phase a substantial increase in the demand of EcoBus rides in the financial-incentives treatment. By contrast, this pattern cannot be observed in the treatment, where no incentives were introduced. The findings are also supported by the bar charts, which show in the financial-incentive treatment, that individual EcoBus rides nearly doubled during the intervention phase

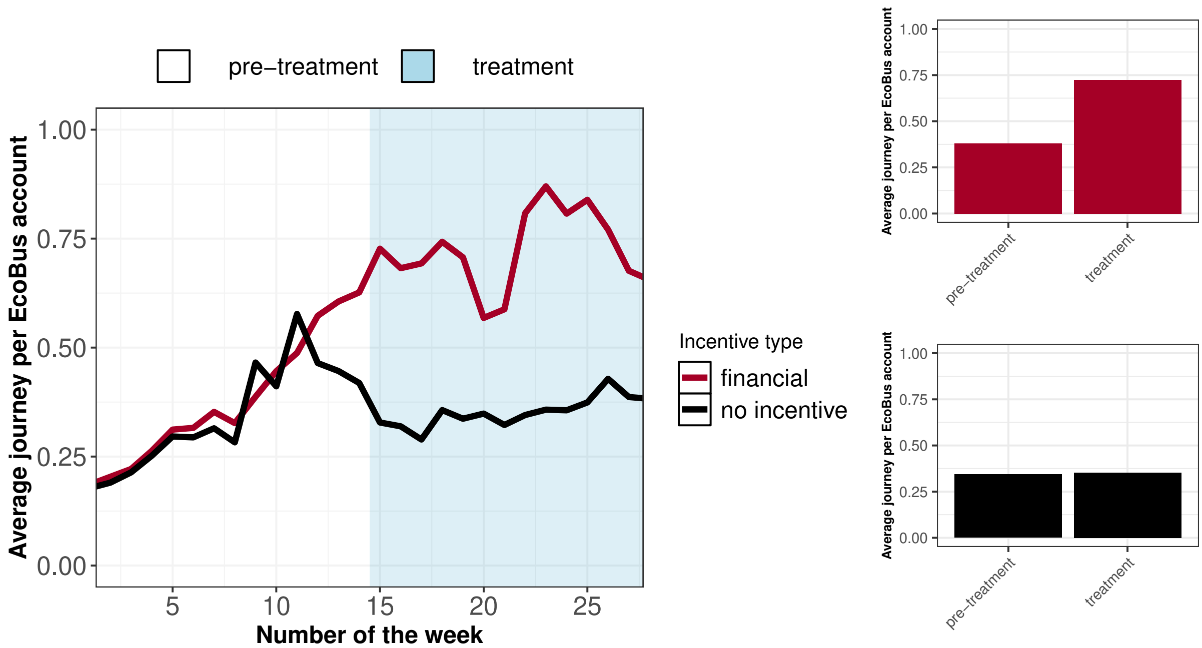


Figure 1 Average completed EcoBus journeys for the financial-incentives and the matched no-incentives groups.

from 0.38 to 0.72. At the same time, we find no difference in the control treatment, where customers, on average, demanded 0.34 rides before the intervention and 0.35 rides during the treatment phase. The findings give a first impression for the test of Hypothesis 1 and the occurrence of potential treatment effects when applying financial incentives.

Next, we turn to the effects of non-financial incentives (Hypothesis 2) on the demand for the EcoBus. Figure 2 shows the actual weekly travel behavior, indicating the means of *weekly EcoBus journeys* of the non-financial incentive group (green line) and the corresponding control group without incentives (black line), which resulted from the matching approach with the non-financial-incentive treatment. The white background indicates the pre-treatment phase (week 1–14), whereas the blue background indicates the treatment phase for the financial incentives (week 15–28). Again, we present the mean figures in bar charts next to the timelines.

Focusing on the pre-treatment phase, it can be seen that there is hardly any difference in the average number of journeys between the non-financial incentive treatment and the matched control treatment. There also seems to be some movement at the end of the pre-treatment phase. This is why we again perform DiD regressions focusing on the pre-treatment phase and using control variables. Interestingly, we find a substantial increase in the demand for EcoBus rides in the treatment with non-financial incentives. Whereas, only a weak increase over time can be observed when no incentives were introduced. These findings are also reflected in the bar charts. Here, we find that the average number of EcoBus rides is more than two times higher (0.42) than in the pre-treatment phase

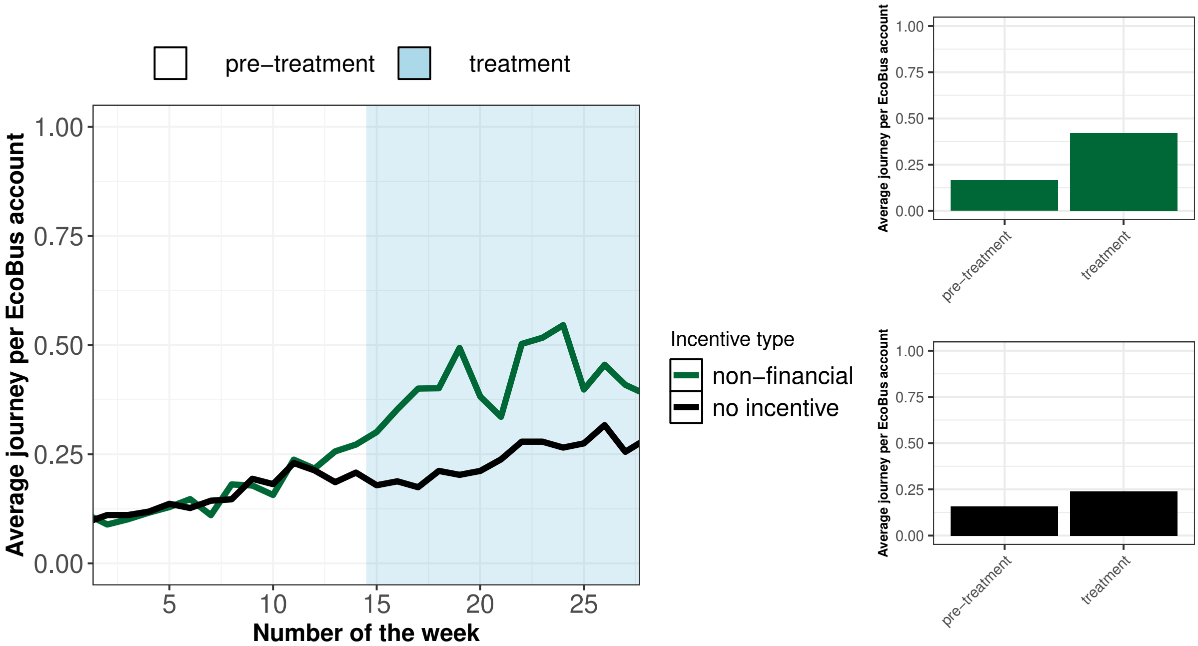


Figure 2 Average completed EcoBus journeys for the non-financial incentives and the matched no-incentives groups.

(0.16). This suggests that non-financial incentives apparently have a similar positive effect to financial incentives. By contrast, only a moderate increase in the average rides can be observed for the control data (from 0.16 to 0.24).

To get deeper insights and to test our hypotheses, we apply DiD regressions using coarsened exact matching. Before that, we ensured that our data were similar in the incentives and control treatments in the pre-treatment phase (weeks 1–14). To do so, we ran OLS regressions (see Table E.1 in the Appendix), applying a common trend assumption testing. Here, we also apply coarsened exact matching. We find no evidence of a different common trend between the financial and non-incentive treatments.[15] Similarly, for the comparison between the non-financial and no-incentive group, we find no clear difference in the common trend.[16]

5.2 Financial/Non-Financial incentives vs. No Incentives

In this section, we apply four OLS regressions to test the effects of introducing financial or non-financial incentives on the demand for EcoBus rides. In all regressions we make use of the Difference-in-Differences (DiD) approach. We follow the model specification of Angrist and Pischke (2008, p. 174f):

[15] The only two significant treatment dummies are negative, which suggests that in these weeks the financial-incentive group demanded fewer EcoBus rides than the control group. A finding which would rather attenuate a possible significant effect of financial incentives for the EcoBus demand.

[16] The only two significant coefficients are opposed and the coefficients are of a similar size.

$$y_{ist} = \alpha + \gamma f_s + \delta d_t + \beta treatment_{st} + \lambda X_{ist} + \epsilon_{ist} \tag{1}$$

$i =$ individual EcoBus account

$s =$ postcode area

$t =$ time period

$y =$ number of successful EcoBus bookings per week

$f \in \{0,1\} = 0$ if no incentive was allocated/ 1 if an incentive was allocated

$d \in \{0,1\} = 27$ dummy variables with 1 for the corresponding week number

$treatment \in \{0,1\} = 14$ dummy variables, which equal 1 when an incentive was applied in the treatment period (weeks 15-28)

$X_1 =$ deleted journeys: average number of journeys a customer deleted, divided by rides. Measure is computed on a weekly base. A deleted journey is a journey, which was not made.

$X_2 =$ travel time: average driving time per ride on a weekly basis (unit: minutes)

$X_3 =$ waiting time: average waiting time per ride on a weekly basis (unit: minutes)

$X_4 =$ additional passenger: average number of other passengers per ride on a weekly basis. The number of other passengers is the total number of persons the booking was made for by a customer.

$X_5 \in \{0,1\} =$ active account: 1 if EcoBus account was already registered

$X_6 \in \{0,1\} =$ certificate requested (silver): 1 if the silver environmental certificate was already requested (at least in the last week)

$X_7 \in \{0,1\} =$ certificate requested (golden): 1 if the golden environmental certificate was already requested (at least in the last week)

$X_8 \in \{0,1\} =$ voucher requested (silver): 1 if the silver voucher was already requested (at least in the last week)

$X_9 \in \{0,1\} =$ voucher requested (golden): 1 if the golden voucher was already requested (at least in the last week)

The standard errors are clustered on the individual and on the postcode level, since the incentives are allocated based on the postcode and the individual customer behavior. The temporal and spatial regression coefficients concerning the DiD approach are not displayed for reasons of conciseness. The *treatment* coefficients can be interpreted as the difference of the effect of incentives on the *weekly EcoBus journeys* compared to no incentives. The results are presented in Table 1. The idea is that models (1) and (4) do not use controls, whereas we add controls on travel behavior in models (2) and (5). Finally, we add further controls on customers' redeeming behavior of vouchers and certificates (models (3) and (6)).

The significant and positive treatment coefficients demonstrate in regressions (1)–(3) that financial incentives work. It can be seen that the EcoBus demand has a substantially stronger increase when financial incentives are introduced, as compared to the no-

Table 1 DiD Models: Financial vs. Control (1-3) Non-Financial vs. Control (4-6)
Coarsened exact matching: Weights based on the aggregated weekly trips in the pre-treatment phase

	Dependent variable: weekly EcoBus journeys					
	financial incentives			non-financial incentives		
	(1)	(2)	(3)	(4)	(5)	(6)
treatment_1	0.363***	0.152***	0.155***	0.114***	0.033	0.035
	(0.047)	(0.057)	(0.056)	(0.037)	(0.048)	(0.048)
treatment_2	0.327***	0.046**	0.049**	0.157**	0.038	0.039
	(0.028)	(0.022)	(0.023)	(0.064)	(0.046)	(0.046)
treatment_3	0.368***	0.095***	0.097***	0.218***	0.092***	0.091***
	(0.033)	(0.027)	(0.026)	(0.060)	(0.034)	(0.033)
treatment_4	0.350***	0.100***	0.101***	0.182***	0.064**	0.058**
	(0.044)	(0.032)	(0.032)	(0.058)	(0.026)	(0.025)
treatment_5	0.334***	0.148***	0.140***	0.283***	0.110	0.097
	(0.045)	(0.045)	(0.045)	(0.108)	(0.067)	(0.060)
treatment_6	0.184**	0.063**	0.047*	0.163***	0.070**	0.051*
	(0.083)	(0.026)	(0.027)	(0.059)	(0.034)	(0.029)
treatment_7	0.230***	0.109***	0.084***	0.090	0.046	0.017
	(0.056)	(0.011)	(0.013)	(0.066)	(0.040)	(0.028)
treatment_8	0.427***	0.241***	0.212***	0.216	0.098	0.068
	(0.056)	(0.057)	(0.055)	(0.138)	(0.066)	(0.055)
treatment_9	0.476***	0.212***	0.170***	0.231*	0.068	0.033
	(0.065)	(0.026)	(0.023)	(0.121)	(0.091)	(0.074)
treatment_{10}	0.415***	0.127***	0.078*	0.273*	0.053	0.014
	(0.062)	(0.043)	(0.043)	(0.146)	(0.081)	(0.066)
treatment_{11}	0.429***	0.216***	0.162***	0.116	−0.040	−0.087**
	(0.063)	(0.026)	(0.027)	(0.098)	(0.046)	(0.037)
treatment_{12}	0.306***	0.152***	0.084***	0.131	−0.027	−0.079
	(0.079)	(0.023)	(0.026)	(0.108)	(0.071)	(0.062)
treatment_{13}	0.254**	0.073**	0.0003	0.146	0.015	−0.055
	(0.105)	(0.032)	(0.031)	(0.100)	(0.055)	(0.040)
treatment_{14}	0.237***	0.092***	0.003	0.095	−0.019	−0.096*
	(0.084)	(0.020)	(0.025)	(0.084)	(0.048)	(0.055)
deleted journeys		0.121***	0.118***		0.077***	0.076***
		(0.005)	(0.005)		(0.024)	(0.025)
travel time		0.047***	0.047***		0.035***	0.035***
		(0.003)	(0.003)		(0.005)	(0.005)
waiting time		0.012***	0.011***		0.011***	0.010***
		(0.003)	(0.003)		(0.002)	(0.002)
additional passenger		0.184**	0.183**		0.160***	0.163***
		(0.071)	(0.071)		(0.050)	(0.048)
active account		0.224***	0.228***		0.102***	0.104***
		(0.019)	(0.019)		(0.010)	(0.010)
voucher requested (silver)			0.945***			
			(0.206)			
voucher requested (golden)			1.660***			
			(0.558)			
certificate requested (silver)						1.154***
						(0.220)
certificate requested (golden)						1.048***
						(0.172)
Constant	0.167***	0.024**	0.024**	0.096***	0.004	0.004
	(0.046)	(0.010)	(0.010)	(0.036)	(0.005)	(0.006)
Observations	71,876	71,876	71,876	55,104	55,104	55,104
R^2	0.017	0.347	0.355	0.012	0.393	0.400
Adjusted R^2	0.017	0.347	0.354	0.011	0.392	0.400
Residual Std. Error	1.321	1.077	1.071	0.831	0.651	0.647
F Statistic	30.161***	811.272***	804.104***	16.034***	755.044***	746.870***

Note: *p<0.1; **p<0.05; ***p<0.01; Standard errors in parentheses

incentives control treatment. This holds in early, middle, and later time periods.
The effects are also robust to the inclusion of controls on traveling (model (2)) and redeeming behavior (model (3)). Every control variable has a positive impact and is significant. The positive impact of *deleted journeys* and *waiting time* might be explained by the fact that people with a high dependency on regular trips with the EcoBus are more likely to accept a higher waiting time and have more patience while booking. Customers who have a longer *travel time* use the EcoBus more often. Interestingly, it can also be seen that a social environment has positive effects, i.e., the coefficients of *additional passenger* are positive and significant. This suggests that people who book in groups more often use the bus. Interestingly, the demand of the EcoBus is not attenuated after customers requested the silver or golden bonus reward (model (3)).
Taken together, models (1)–(3) confirm the previous results of Figure 1, i.e., the financial incentives have a positive effect on the demand of the EcoBus service. This confirms Hypothesis 1.

Result 1: *The introduction of financial incentives leads to a substantially higher increase in EcoBus rides compared to the no-incentives group. The increase is more pronounced in each week of the treatment phase.*

Regarding the effects of non-financial incentives, model (4) confirms the pattern observed in Figure 2. That is, the coefficients of the early treatment dummies (1–6) are positive and significant. Thus, the non-financial incentives lead to a higher increase in the early periods, as compared to the case without incentives. Afterward, the positive effect is attenuated over time. Nevertheless, all treatment dummies of the subsequent weeks of the intervention are positive. Moreover, the treatment dummies 9 and 10 are significant at the 10-percent level. Model (5) highlights that this is also robust to the inclusion of controls on traveling behavior, i.e., treatment dummies 3, 4, and 6 are significant and have a positive sign. When we control for the impacts of customers' redeeming behavior (model (6)), we find evidence of a reverse effect. In the early periods (treatment dummies 3, 4, and 6) we again find support for the positive effects of non-financial incentives. However, it can be seen that at the end of the treatment phase non-financial incentives apparently become less effective. In weeks 11 and 14, we observe a significant negative effect in comparison to the non-incentives benchmark. An explanation may be that the non-incentive treatment applies an environmental framing, i.e., the certificates provide information on the saved amounts of CO2. This may emphasize the positive effects of the bus service on sustainability. In that case, it is possible that customers who redeemed the certificates and experienced the environmental framing become disappointed in the late periods. The reason is that those subjects may have an increased awareness of the good cause of the EcoBus and now realize that this service would soon be stopped. Thus, we believe that the decline in the late periods of the non-financial treatment may be a sort of a motivational crowding-out effect, which is induced in the end by the environmental framing of the certificates. In summary, we find support for Hypothesis 2 in early periods, whereas the positive effect is attenuated at the end of the treatment phase. Overall, the findings suggest that financial incentives are more effective than non-financial incentives.

Result 2: *The introduction of non-financial incentives leads to a more pronounced increase in early periods compared to the no-incentives group. The effect is attenuated in the late periods of the intervention phase.*

5.3 Financial Incentives vs. Non-Financial Incentives

Before we analyze the impact of financial vs. non-financial incentives, we again ensured that our data were similar in the pre-treatment phase of the two treatments. This is supported by an OLS regression (see Table E.2 in the Appendix), which applies a common trend assumption testing. The regression emphasizes that no different trend occurs between the two treatments. We find that six of the seven treatment dummies are insignificant. The only exception is treatment dummy 1, which is negative and weakly significant, i.e., in the first period of the pre-treatment phase there is a slightly higher demand in the non-financial incentives treatment.

To explore whether financial incentives outperform non-financial incentives, we conduct OLS DiD regressions. The regressions are based on the same models as in Table 1. The main difference is that in these regressions we do not apply coarsened exact matching, as subjects in the financial- and non-financial treatments were randomized by the same procedure, based on the postcode they entered.

Table 2 presents the models. The standard errors are clustered on the postcode level, since the incentives are allocated depending on the postcode. The *treatment* coefficients can be interpreted as the difference of the effect of financial incentives on the *weekly EcoBus journeys* compared to the non-financial incentives.

The results show in regressions (1), (2), and (3) that all *treatment* coefficients are positive. Furthermore, the treatment weeks 1, 4, 6, 7, 11, 12, 13, and 14 are significant in the first regression, the treatment weeks 6, 8, 10, 11, 12, 13, and 14 are significant in the second regression, and the treatment weeks 5 to 14 are significant in the third regression. Overall, the three models support the impression of the previous findings, i.e., financial incentives outperform non-financial incentives, especially at middle and later time periods.

Every control variable has a positive impact and is significant at the one percent level except the variable *deleted journeys* in regressions (2) and (3), which is significant at the five percent level.

Again, we find a positive impact of the control variables. Furthermore, we take into consideration the odds that arise when the requested bonuses are set in proportion to the available bonuses. Out of 86, 39 requested the silver environmental certificate, and 19 of

Table 2 DiD Model: Financial vs. Non-Financial Incentives

	Dependent variable: weekly EcoBus journeys		
	(1)	(2)	(3)
$treatment_1$	0.194***	0.101	0.102
	(0.064)	(0.082)	(0.081)
$treatment_2$	0.123	0.015	0.018
	(0.087)	(0.052)	(0.053)
$treatment_3$	0.085	0.011	0.025
	(0.091)	(0.070)	(0.062)
$treatment_4$	0.119**	0.061	0.088
	(0.059)	(0.065)	(0.063)
$treatment_5$	0.027	0.094	0.119*
	(0.093)	(0.078)	(0.068)
$treatment_6$	0.068*	0.080***	0.107***
	(0.038)	(0.030)	(0.021)
$treatment_7$	0.123**	0.065	0.096***
	(0.053)	(0.041)	(0.027)
$treatment_8$	0.121	0.122**	0.147***
	(0.109)	(0.057)	(0.048)
$treatment_9$	0.122	0.120	0.139*
	(0.095)	(0.114)	(0.084)
$treatment_{10}$	0.124	0.159**	0.178***
	(0.126)	(0.080)	(0.059)
$treatment_{11}$	0.285***	0.309***	0.333***
	(0.069)	(0.057)	(0.057)
$treatment_{12}$	0.182**	0.259***	0.280***
	(0.084)	(0.071)	(0.064)
$treatment_{13}$	0.112*	0.157***	0.200***
	(0.066)	(0.047)	(0.030)
$treatment_{14}$	0.136**	0.165***	0.195***
	(0.053)	(0.050)	(0.071)
deleted journeys		0.068**	0.063**
		(0.027)	(0.026)
travel time		0.054***	0.053***
		(0.004)	(0.004)
waiting time		0.012***	0.011***
		(0.002)	(0.002)
additional passenger		0.152***	0.156***
		(0.053)	(0.042)
active account		0.265***	0.279***
		(0.023)	(0.020)
certificate requested (silver)			1.190***
			(0.266)
certificate requested (golden)			1.589***
			(0.227)
voucher requested (silver)			1.062***
			(0.209)
voucher requested (golden)			2.195***
			(0.649)
Constant	0.140*	−0.004	−0.002
	(0.074)	(0.026)	(0.026)
Observations	39,900	39,900	39,900
R^2	0.019	0.348	0.376
Adjusted R^2	0.017	0.347	0.375
Residual Std. Error	1.496	1.220	1.194
F Statistic	17.900***	452.473***	470.017***
Note:	*p<0.1; **p<0.05; ***p<0.01; Standard errors in parentheses		

43 requested the golden certificate. In contrast, 81 of 300 available silver vouchers and 42 of 166 available golden vouchers were requested. Compared to the financial incentive, the probability of a requested incentive is higher for the non-financial incentives. In summary, we find evidence that financial incentives outperform non-financial incentives. The treatment dummies show that this especially materializes at the end of the treatment phase. This adds additional support to our previous finding, i.e., the effects of non-financial incentives are attenuated at the end of the intervention. By contrast, financial incentives permanently increase the demand for the EcoBus rides. In summary, we confirm Hypothesis 3.

Result 3: *Financial incentives are more effective than non-financial incentives in increasing the EcoBus demand. Financial incentives also work in late periods.*

5.4 Robustness checks

In this section we report the results of robustness checks for Table 1 and Table 2. The DiD regressions in Table 1 are based on coarsened exact matching where the incentive types were independently matched to the control group, based on the similarity of aggregated weekly trips in the pre-treatment phase. In this respect, we conducted regressions using an alternative matching, based on the driving characteristics of the passengers. For each control variable two values are included in the matching (see also Nielsen, 2020). Thus, the groups differ as little as possible in terms of their driving characteristics. The control variables are based on the pre-treatment, or on the treatment time period per journey. In addition, the active account variables include the corresponding aggregated number of weeks, i.e., values between 0 and 14. We ran two regressions (model (1): financial incentives vs. no incentives; model (2): non-financial incentives vs. no incentives). The results are presented in Table F.1 in the Appendix. The results of the financial incentives treatment confirm the robustness of the findings in Table 1. That is, 11 of 14 treatment variables are positive and seven are significant. Similarly, we confirm that non-financial incentives also have a positive effect on the EcoBus demand. Here, we find that 10 of 14 treatment dummies are positive and nine are significant.

Another robustness check concentrates on the randomization procedure, i.e., we test whether customers who live in the most attractive area (Claustahl) may have biased the findings. The idea was that the region in Clausthal should be divided again into both types of incentives. In this case, the first trip in the treatment phase should be used to differentiate between east and west in Clausthal for those persons who had already indicated the postcode of Clausthal. However, due to a technical error, the customers of the Clausthal region only received financial incentives. This means that people in Clausthal who had entered a Clausthal postcode had to make a first trip and log in again to receive the financial incentive.[17] In the robustness check, we analyze whether treatment differences between financial- and non-financial incentives hold when we exclude the Clausthal sample. In this regard, the EcoBus accounts from the center of the pilot phase Clausthal (see Table F.2 in Appendix) are removed. All in all, the regressions are similar to the findings in Table 2. When all necessary controls are included, model (2) shows that six of the 14 treatment dummies are positive and significant. This emphasizes that the results are robust, i.e., financial incentives outperform non-financial incentives, even when excluding the attractive area of Clausthal. Furthermore, in the regression without Clausthal, the treatment dummies of the earlier time periods indicate a higher success of the non-financial incentive.[18] To validate the robustness of the findings of Table 2, additional model variations are conducted (see Bertrand et al., 2004). Firstly, optimized clustered standard errors based on Pustejovsky and Tipton (2018) are used to tackle the problem of a small number of clusters and unbalanced clusters. Secondly, the 28 weeks are aggregated to two time periods. Thirdly, we have removed the EcoBus account from outside the service area, from the limited service area, from the estimated postcodes, and late registrations. The findings are all in all in line with the findings of Table 2.

5.5 Survey analysis

5.5.1 Demographics and Preferences

To get a better understanding of customers' preferences for the reward types we conducted a survey. Another goal was to learn more about subjects' interest in environmental issues. To collect these data, we asked EcoBus customers in the app to voluntarily participate in the questionnaire. Overall, in our data there are 194 observations (58 female; 133 male),[19] which can be used for the analysis.[20] Focusing on the demographics, we find that the average age is 31.71 years. Only 50 persons live in an urban or rather urban area. The mean number of children per household is 0.54, and the mean number of adults per household is 2.29. The majority are rather well educated; 108 people have a high school diploma or similar or even a college or university degree. However, 75 people have a budget of less than 800 Euros per month.

Regarding participants' preferred reward types, we find that the majority (145 persons) appreciate vouchers over certificates (52 persons). In this regard, participants could give

[17]Doing a re-login was necessary when customers gave a Clausthal postcode. If these subjects did not re-login, they were automatically allocated to the non-incentive treatment

[18]This is demonstrated by the only negative significant treatment dummy of period 3.

[19]Three subjects did not answer the gender question.

[20]We carefully eliminated double entries concerning the customer ID and entries from participants who declared that it was not possible to fill out the questionnaire. We also did not use questionnaires, which were not completed. Furthermore, one data set was not used because of using the proposed minimum value of the customer ID. The survey tool suggested a minimum value after the person had not entered anything in the question about the EcoBus customer ID.

more than one possible answer. The data show that in most multiperson households (58.57%) more than one person used the EcoBus. Out of the multiperson households, 47.14% used the EcoBus together with other household members (see also Skarin et al., 2017). Subjects' habit of not riding alone may explain the positive effects of additional passengers, which we found in the regressions. In the questionnaire, we also asked questions on subjects' efforts to protect the environment. The data suggest that environmental protection is an important issue for the customers, although their knowledge is not profound. This is reflected in a question where subjects had to guess the share of greenhouse gas emissions caused by the traffic in Germany. Subjects guessed 34.35% though the correct share is 19% (see Federal Environment Agency of Germany, 2020). The finding that citizens have a bad knowledge of climate politics in Germany is in line with the study of Brüggeman et al. (2017). It can be summarized that subjects' preferences for vouchers are in line with the better performance of financial incentives. Moreover, subjects' concern for the protection of the environment and their lack of precise information on environmental issues may explain why even non-financial certificates motivate customers. Not only might they give them a feeling of protecting the environment, but they also receive precise information on their contribution toward protecting the environment.

5.5.2 Travel Pattern and Purpose of Use

The survey reveals that the participants complete 11.91 rides per week, on average, for all different kinds of transport modes. A round trip counts as two completed rides. 45.88 % of the survey participants use mainly single tickets, and 23.20 % use multiple discount tickets (for 2, 4, 8 or 10 rides). The others use daily, monthly or other types of subscription models. The participants were also asked what transport modes were available for subjects and what transport modes they regularly used. Multiple answers were possible. The bus and EcoBus show a very similar pattern in terms of their high availability and high regular usage. Another conspicuous finding is the high regular car usage. This supports the notion that people living in a rural area depend on their own car, as they have poor access to public transportation. This is also supported by the high demand for the EcoBus, reflected by the high number subjects' regular usage. Moreover, the majority of the participants state in the survey that they have a bad perception of the local transport system.

In terms of subjects' usage of the EcoBus, we find that most of them use it for recreational activities. Work, shopping, education, doctors visits and other purposes are mentioned as well, but the EcoBus is only moderately chosen for those purposes. Regarding the motivation to use the EcoBus, the following factors play a role. The predominant reason is flexibility. Furthermore, quickness, low costs, and protecting the environment are important factors followed by curiosity, no alternative, and others (an overview of customers' answers is reported in Figure G.1 of the Appendix). Furthermore, 67.01 % of the subjects agrees with one of the two categories: “the EcoBus is environmentally,” or “rather environmentally friendly.” The importance of environmental factors may explain why the non-financial incentives work to increase the demand.

6 Discussion

Our findings clearly support Hypothesis 1, highlighting the positive effect of financial incentives to increase the demand for a DRT service. At the same time, the evidence is less clear when focusing on Hypothesis 2. We find some support for the hypothesis, indicating that even non-financial incentives may have positive effects on the demand for the EcoBus. However, this is especially the case in the early periods and the effect even becomes moderately negative in the late periods of the treatment phase. An explanation may be that a sort of motivational crowding-out effect may be in place (Gneezy et al., 2011). Over time, it is possible that subjects’ motivation is attenuated in the presence of non-financial incentives. Moreover, when customers receive environmental certificates they are reminded of the positive effects of the bus rides in protecting the environment. However, at the end of the treatment phase all customers of the EcoBus service were informed that the pilot phase of the EcoBus project would soon stop. We speculate that this may have had a negative effect on customers in the non-financial treatment, as this treatment was environmentally framed. In this respect, customers may have become disappointed and showed motivational crowding-out effects when realizing that a project which has positive effects on the environment would be stopped.

The results find support for Hypothesis 3. That is, the financial incentives increase the average usage in comparison to the non-financial incentives, especially during middle and later time periods. This corresponds to the observations of Ito et al. (2015), Masclet et al. (2003) and Dolan and Metcalfe (2015), which show that financial incentives perform better at later time periods or time periods outside the treatment phase. The effect might be explained by a higher motivation to achieve the levels to get the financial benefit. Furthermore, the difference between the two incentive treatments may also be spurred by the fact that the intrinsic motivation of the customers in the non-financial incentive treatment shrinks at the near end of the pilot phase. This crowding-out effect is likely, since the comparison of the non-financial incentives with the control group supports this reasoning for the last four treatment weeks. It may be worthwhile designing more advanced non-financial incentives that include specific information and address other dimensions, such as costs (see Graham et al., 2011). Overall, the data suggest that incentives work to increase the demand for the DRT, which is also mirrored in the development of customers’ telephone bookings over time. Here, we find a clear decline after the treatment phase started and several app users were offered the incentives (see Figure H.1 in the Appendix). We speculate that customers substituted the telephone bookings with internet bookings in order to receive the incentives.

7 Conclusion

This paper investigated the effects of financial and non-financial incentives on the travel behavior of DRT customers. The findings provide further insights for the impact of incentives in the field of new sustainable transport modes, such as the DRT service. The findings emphasize the importance of incentives and gamification environments for increasing the demand for new mobility projects, especially during their pilot phase. Our results of the financial incentives have a persistent and strong effect on the increase of the demand for the DRT service. Interestingly, we also find that even non-financial incentives have the potential to stimulate the demand for the EcoBus. We exploit the environmental character of the service to save carbon emissions and reward customers with environmentally framed certificates. However, the findings show that especially at the end, the effect is attenuated and moderately reversed. That is, it is possible that motivational crowding-out effects may be in place. Hence, these findings should be taken with a grain of salt. As a consequence, we find that financial incentives outperform non-financial incentives, as financial incentives are especially effective at the very end. The findings therefore provide important policy implications. We find that promoting new sustainable transport modes with financial incentives in the form of vouchers may pay off. This may help to motivate the customers, which especially materializes in late periods. We also show that non-financial incentives also have the potential to boost the DRT demand among customers who are intrinsically motivated. The findings show that the environmental character of the service can be exploited by a non-financial reward system which uses an environmental framing. However, we also highlight that policymakers should be aware of the potential danger of the attenuated effects in the long-run.

This provides an avenue for potential future research. First, it would be interesting to explore more deeply the potential underlying channels of the effects of intrinsic motivation in the context of the environmentally framed non-financial incentive treatment. Second, it is important to find ways to stabilize the positive effects of non-financial incentives over time. In this respect, it may pay off to apply more voucher options and specific and multidimensional non-financial incentives. Future research may also analyze the impact of incentives on different user groups in terms of travel behavior, personal environment, the motivation of transport mode choices, and demographic characteristics.

Acknowledgments

We would like to thank the software development team of the *Max Planck Institute for Dynamics and Self-Organization* for the implementation of this field experiment. In this respect, we especially want to thank the HAWK Göttingen and Fabian Maus for his programming activities. Furthermore, we would like to explicitly thank the leisure facilities for the thoughtful, friendly and professional cooperation and for the provision of the vouchers.

Technical Note: The data cleaning, the calculations and the visualizations were carried out with the help of R and extensions (see R Core Team, 2019). In particular, the R-package stargazer (to visualize the regression tables) and the R-package ggplot2 (to visualize the graphs) are to be mentioned here (see Hvalac, 2018, and Wickham, 2016).

Funding: The EcoBus project itself was financially supported by the *Südniedersachsenprogramm* and the *European Regional Development Fund*. The research itself was funded by the *Max Planck Society*.

Data availability statement

The data sets cannot be made public. The data that has been used is confidential. This is because of data protection concerns, as very personal data such as addresses are part of the travel data sets. Furthermore, it would be possible to combine the travel data with personal data from the questionnaire.

Declaration of interest statement

Declarations of interest: none

References

Allcott, H., & Rogers, T. (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review, 104(10)*, 3003-37.

Anagnostopoulou, E., Bothos, E., Magoutas, B., Schrammel, J., & Mentzas, G. (2016). Persuasive technologies for sustainable urban mobility. *arXiv preprint arXiv:1604.05957.*

Andrés, L., & Padilla, E. (2018). Driving factors of GHG emissions in the EU transport activity. *Transport Policy, 61*, 60-74.

Angrist, J. D., & Pischke, J. S. (2008). Mostly harmless econometrics: An empiricist's companion. Princeton university press.

Ariely, D. (2008). Predictably irrational: The hidden forces that shape our decisions. HarperCollins.

Ariely, D., Gneezy, U., Loewenstein, G., & Mazar, N. (2009). Large stakes and big mistakes. *The Review of Economic Studies, 76(2)*, 451-469.

Asensio, O. I., & Delmas, M. A. (2015). Nonprice incentives and energy conservation. *Proceedings of the National Academy of Sciences, 112(6)*, E510-E515.

Bamberg, S. (2006). Is a residential relocation a good opportunity to change people's travel behavior? Results from a theory-driven intervention study. *Environment and behavior, 38(6)*, 820-840.

Bareket-Bojmel, L., Hochman, G., & Ariely, D. (2017). It's (not) all about the Jacksons: Testing different types of short-term bonuses in the field. *Journal of Management, 43(2)*, 534-554.

Baumann, H., & Seils, E. (2019). Verfügbare Haushalteinkommen im regionalen Vergleich. `https://www.boeckler.de/pdf/wsi_vm_verfuegbare_einkommen.pdf` (last accessed on 2020-06-03).

Berg, J., & Ihlström, J. (2019). The Importance of Public Transport for Mobility and Everyday Activities among Rural Residents. Social Sciences, 8(2), 58.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates?. *The Quarterly journal of economics, 119(1)*, 249-275.

Bolderdijk, J. W., & Steg, L. (2015). 21. Promoting sustainable consumption: the risks of using financial incentives. *Handbook of research on sustainable consumption*, 328-342.

Bowden, H., & Hellen, G. (2019). A data driven, segmentation approach to real world travel behaviour change, using incentives and gamification. In Towards User-Centric Transport in Europe (pp. 173-182). Springer, Cham.

Bowles, S., & Polania-Reyes, S. (2012). Economic incentives and social preferences: substitutes or complements?. *Journal of Economic Literature, 50(2)*, 368-425.

Brake, J., Nelson, J. D., & Wright, S. (2004). Demand responsive transport: towards the emergence of a new market segment. *Journal of Transport Geography, 12(4)*, 323-337.

Brüggemann, M., De Silva-Schmidt, F., Hoppe, I., Arlt, D., & Schmitt, J. B. (2017). The appeasement effect of a United Nations climate summit on the German public. *Nature climate change, 7(11)*, 783.

Buningh, S., Martijnse-Hartikka, R., & Christiaens, J. (2014, April). Mobi-modal shift through gamification. In Transport Research Arena (TRA) 5th Conference: Transport Solutions from Research to Deployment.

Chapman, L. (2007). Transport and climate change: a review. *Journal of transport geography, 15(5)*, 354-367.

Charness, G., & Gneezy, U. (2009). Incentives to exercise. *Econometrica, 77(3)*, 909-931.

Davison, L., Enoch, M., Ryley, T., Quddus, M., & Wang, C. (2012). Identifying potential market niches for Demand Responsive Transport. *Research in Transportation Business & Management, 3,* 50-61.

Dolan, P., & Metcalfe, R. (2015). Neighbors, knowledge, and nuggets: two natural field experiments on the role of incentives on energy conservation. *Becker Friedman Institute for Research in Economics Working Paper*, (2589269).

EcoBus team (2018). Wohin fährt der EcoBus? `https://www.ecobus.jetzt/informationen.html#wohin-faehrt-der-ecobus` (last accessed on 2020-06-03).

Enoch, M., Potter, S., Parkhurst, G., & Smith, M. (2006). Why do demand responsive transport systems fail?

Falk, A. (2007). Gift exchange in the field. *Econometrica, 75(5)*, 1501-1511.

Federal Environment Agency of Germany (2020). Emmisionsquellen. https://www.umweltbundesamt.de/themen/klima-energie/klimaschutz-energiepolitik-in-deutschland/treibhausgas-emissionen/emissionsquellen#textpart-1 (last accessed on 2020-06-03).

Federal Environment Ministry of Germany (2018). Weitere 130 Millionen Euro für saubere Luft und modernen ÖPNV-Pressemitteilung Nr. 165/18 Luftreinhaltung. https://www.bmu.de/pressemitteilung/weitere-130-millionen-euro-fuer-saubere-luft-und-modernen-oepnv/ (last accessed on 2020-06-03).

Federal Institute for Research on Building, Urban Affairs and Spatial Development (2017). Raumgliederungen auf Kreisbasis- Kreise und kreisfreie Städte, Kreisregionen. https://www.bbsr.bund.de/BBSR/DE/Raumbeobachtung/Downloads/downloads_node.html (last accessed on 2020-06-03).

Festré, A., & Garrouste, P. (2015). Theory and evidence in psychology and economics about motivation crowding out: A possible convergence?. *Journal of Economic Surveys, 29(2)*, 339-356.

Frey, B. S., & Oberholzer-Gee, F. (1997). The cost of price incentives: An empirical analysis of motivation crowding-out. *The American economic review, 87(4)*, 746-755.

Fujii, S., & Kitamura, R. (2003). What does a one-month free bus ticket do to habitual drivers? An experimental analysis of habit and attitude change. *Transportation, 30(1)*, 81-95.

Gneezy, U., Meier, S., & Rey-Biel, P. (2011). When and why incentives (don't) work to modify behavior. *Journal of Economic Perspectives*, 25(4), 191-210.

Gneezy, U., & Rey-Biel, P. (2014). On the relative efficiency of performance pay and noncontingent incentives. *Journal of the European Economic Association, 12(1)*, 62-72.
Gneezy, U., & Rustichini, A. (2000). Pay enough or don't pay at all. *The Quarterly Journal of Economics, 115(3)*, 791-810.

González, P. F., Landajo, M., & Presno, M. J. (2014a). Tracking European Union CO2 emissions through LMDI (logarithmic-mean Divisia index) decomposition. The activity revaluation approach. *Energy, 73*, 741-750.

González, P. F., Landajo, M., & Presno, M. J. (2014b). The driving forces behind changes in CO2 emission levels in EU-27. Differences between member states. *Environmental Science & Policy, 38*, 11-16.

Graham, J., Koo, M., & Wilson, T. D. (2011). Conserving energy by inducing people to drive less. *Journal of Applied Social Psychology, 41(1)*, 106-118.

Hunecke, M., Blöbaum, A., Matthies, E., & Höger, R. (2001). Responsibility and environment: Ecological norm orientation and external factors in the domain of travel mode choice behavior. *Environment and Behavior, 33(6)*, 830-852.

Hlavac, M. (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables. R package version 5.2.2. Central European Labour Studies Institute (CELSI). Bratislava, Slovakia. `https://CRAN.R-project.org/package=stargazer` (last accessed on 2020-06-03)

Ito, K., Ida, T., & Tanaka, M. (2015). The persistence of moral suasion and economic incentives: field experimental evidence from energy demand (No. w20910). National Bureau of Economic Research.

King, G., & Nielsen, R. (2019). Why propensity scores should not be used for matching. *Political Analysis, 27(4)*, 435-454.

Kosfeld, M., & Neckermann, S. (2011). Getting more work for nothing? Symbolic awards and worker performance. *American Economic Journal: Microeconomics, 3(3)*, 86-99.

Lacetera, N., & Macis, M. (2010). Do all material incentives for pro-social activities backfire? The response to cash and non-cash incentives for blood donations. *Journal of Economic Psychology, 31(4)*, 738-748.

Lacetera, N., Macis, M., & Slonim, R. (2012). Will there be blood? Incentives and displacement effects in pro-social behavior. *American Economic Journal: Economic Policy, 4(1)*, 186-223.

Liobikiené, G., & Butkus, M. (2017). The European Union possibilities to achieve targets of Europe 2020 and Paris agreement climate policy. *Renewable Energy, 106*, 298-309.

Local authority Braunlage (2018). Die Stadt Braunlage in Zahlen, 2018. `https://www.stadt-braunlage.com/28-stadtinfo/zahlen-und-fakten/19-braunlage-zahlen` (last accessed on 2020-06-03).

Local authority Goslar (2017). Einwohner der Gemeinden und Ortsteile. https://www.landkreis-goslar.de/media/custom/94_4556_1.PDF?1527158415 (last accessed on 2020-06-03).

Local authority Osterode (2012). Ortschaften der Stadt Osterode am Harz. https://www.osterode.de/leben-in-osterode-am-harz/ortschaften/ (last accessed on 2020-06-03).

Local transport authority RBB (n.y.). Harz Übersichtskarte mit RBB Linien. https://www.rbb-bus.de/regiobusbs/view/mdb/regiobusbs/pdf/MDB70978-karte_vgharz__201009.pdf (last accessed on 2020-06-03).

Local transport authority VSN (n.y.). Fahrpläne für die Überlandbusse. https://vsninfo.de/de/fahrplaene (last accessed on 2020-06-03).

Maréchal, M. A., & Thöni, C. (2018). Hidden persuaders: do small gifts lubricate business negotiations?. *Management Science.*

Martyn-Hemphill, A. & Kelly, N. (2018). The city that gives you free beer for cycling. https://www.bbc.com/news/av/stories-45940844/the-city-that-gives-you-free-beer-for-cycling (last accessed on 2020-06-03).

Masclet, D., Noussair, C., Tucker, S., & Villeval, M. C. (2003). Monetary and nonmonetary punishment in the voluntary contributions mechanism. *American Economic Review, 93(1)*, 366-380.

Mellström, C., & Johannesson, M. (2008). Crowding out in blood donation: was Titmuss right?. *Journal of the European Economic Association, 6(4)*, 845-863.

Meier, S. (2007). Do subsidies increase charitable giving in the long run? Matching donations in a field experiment. *Journal of the European Economic Association, 5(6)*, 1203-1222.

Nielsen, R. A. (2020). Statistical Matching with Time-Series Cross-Sectional Data: Magic, Malfeasance, or Something in Between? IN: Curini, L., & Franzese, R. (Eds.). (2020). The SAGE Handbook of Research Methods in Political Science and International Relations. SAGE.

Nyga, A., Minnich, A., & Schlüter, J. (2020). The effects of susceptibility, eco-friendliness and dependence on the Consumers' Willingness to Pay for a door-to-door DRT system. *Transportation Research Part A: Policy and Practice, 132*, 540-558.

Percy, J. (1872). Die Metallurgie : Gewinnung und Verarbeitung der Metalle und ihrer Legirungen, in praktischer und theoretischer, besonders chemischer Beziehung. Vieweg.

Pustejovsky, J. E., & Tipton, E. (2018). Small-sample methods for cluster-robust variance estimation and hypothesis testing in fixed effects models. *Journal of Business & Economic Statistics, 36(4)*, 672-683.

R Core Team (2019). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. Vienna, Austria. `https://www.R-project.org` (last accessed on 2020-06-03).

Skarin, F., Olsson, E. L., Roos, I., & Friman, M. (2017). The household as an instrumental and affective trigger in intervention programs for travel behavior change. *Travel Behaviour & Society, 6*, 83-89.

State Office for Statistics Lower Saxony (2019a). 12412 - Bevölkerungsvorausberechnungen. `https://www1.nls.niedersachsen.de/statistik/html/default.asp` (last accessed on 2020-06-03).

State Office for Statistics Lower Saxony (2019b). 45412 - Betriebe; Ankünfte; Übernachtungen; Aufenthaltsdauer; Schlafgelegenheitenauslastung nach Betriebsart (Reisegebiet) . `https://www1.nls.niedersachsen.de/statistik/html/default.asp` (last accessed on 2020-06-03).

Suche Postleitzahl team (2018). Grenzen als Shapefile. `https://www.suche-postleitzahl.org/downloads` (last accessed on 2020-06-03).

Thøgersen, J., & Møller, B. (2008). Breaking car use habits: The effectiveness of a free one-month travelcard. *Transportation, 35(3)*, 329-345.

Titmuss, R. M. (1970). The Gift Relationship. London: Allen and Unwin.

Velaga, N. R., Nelson, J. D., Wright, S. D., & Farrington, J. H. (2012). The potential role of flexible transport services in enhancing rural public transport provision. *Journal of Public Transportation, 15(1)*, 7.

Wickham, H. (2016). ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York. `https://ggplot2.tidyverse.org` (last accessed on 2020-06-03)

Yen, B. T., Mulley, C., & Burke, M. (2019). Gamification in transport interventions: Another way to improve travel behavioural change. *Cities, 85*, 140-149.

Appendices

Appendix A

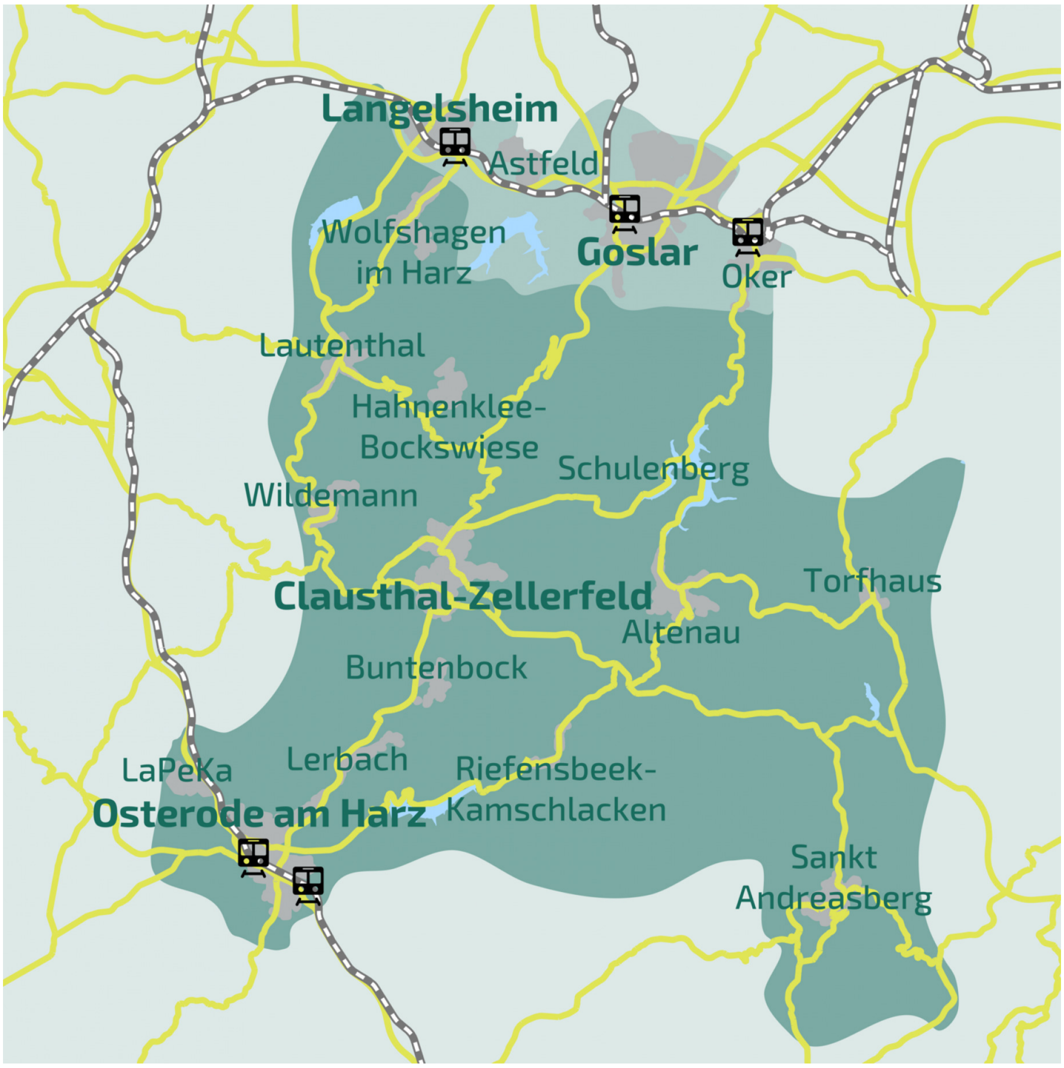


Figure A.1 Service area of the second EcoBus pilot phase: Full service (dark green), booking constraint (light green). Source: EcoBus Team 2018.

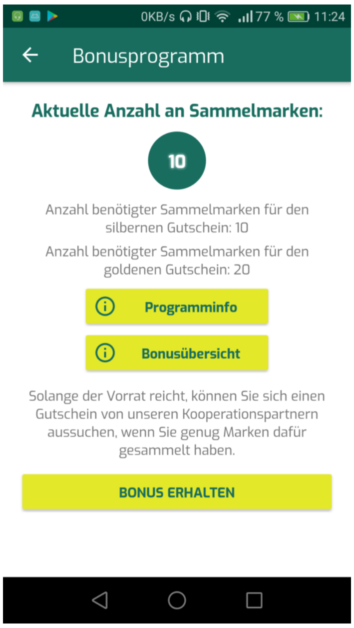
Appendix B

travel behavior	personal environment
EN01 EcoBus ticket EN02 mobile phone ownership EN03 quality internet EN04 public transport supply EN05 average weekly transport use EN06 availability of transport modes EN07 usage of transport modes EN08 purpose of EcoBus usage EN09 willingness to pay (different modes) EN10 appreciation of bus system EN11 appreciation EcoBus EN12 suggestion for improvement (EcoBus)	UN01 solitarily or not UN02 number of room mates UN03 EcoBus users (room mates) UN04 using together EcoBus UN05 number of friends using EcoBus UN06 telling others about EcoBus UN07 reaction
motivation	demographic information
ME01 main reason using EcoBus ME02 price comparison alternative ME03 travel time comparison ME04 private environment protection ME05 importance environment protection ME06 comparison personal environment ME07 EcoBus eco-friendly ME08 knowledge question about pollution	DV01 gender DV02 age DV03 education DV04 living environment DV05 service area DV06 monthly budget DV07 political party DV08 voucher/certificate DV09 constumer ID
others	
AA01 seriously answered AA03 results and lottery	

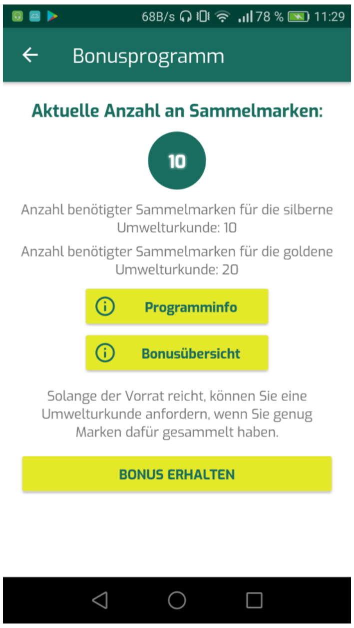
Table B.1 Overview of the variables from the questionnaire

Appendix C

Appendix C.1

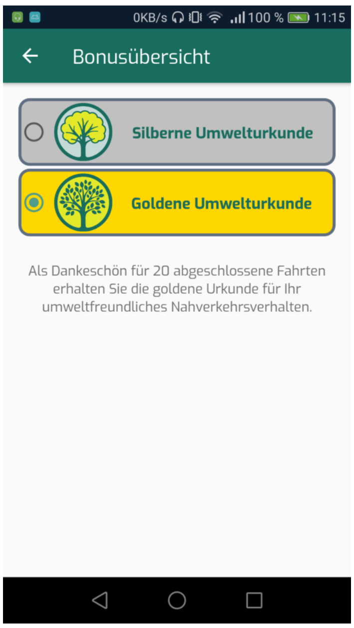


(a) Android main page (financial incentive)



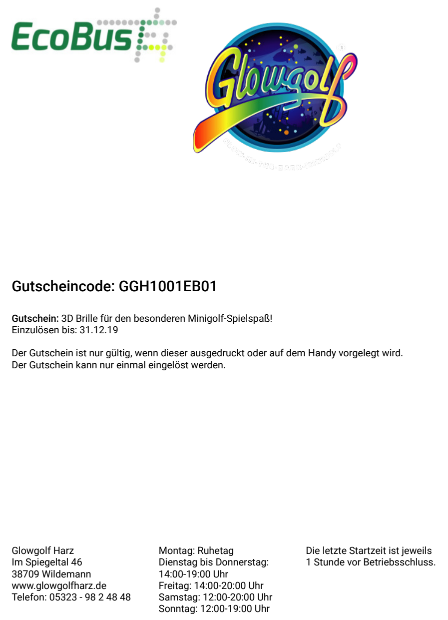
(b) Android main page (non-financial incentive)

(c) Android overview of the incentives (financial incentive)



(d) Android overview of the incentives (non-financial incentive)

Figure C.1 Main page of the financial incentive (a) and the non-financial incentive (b) and overview of the incentives (financial) (c) and overview of the incentives (non-financial) (d); exemplary for Android.



Gutscheincode: GGH1001EB01

Gutschein: 3D Brille für den besonderen Minigolf-Spielspaß!
Einzulösen bis: 31.12.19

Der Gutschein ist nur gültig, wenn dieser ausgedruckt oder auf dem Handy vorgelegt wird.
Der Gutschein kann nur einmal eingelöst werden.

Glowgolf Harz
Im Spiegeltal 46
38709 Wildemann
www.glowgolfharz.de
Telefon: 05323 - 98 2 48 48

Montag: Ruhetag
Dienstag bis Donnerstag:
14:00-19:00 Uhr
Freitag: 14:00-20:00 Uhr
Samstag: 12:00-20:00 Uhr
Sonntag: 12:00-19:00 Uhr

Die letzte Startzeit ist jeweils
1 Stunde vor Betriebsschluss.

(a) Example of a silver incentive (financial)

Silberne Umwelturkunde für zehn abgeschlossene Fahrten

Liebe/r EcoBus-Nutzer/in,
vielen Dank, dass Sie sich für ein umweltfreundlicheres Nahverkehrskonzept entschieden haben und mit dem EcoBus fahren. Sie haben seit der Einführung des Bonusprogramms bereits zehn Umweltmarken gesammelt:

Pro gefahrenem Kilometer mit dem EcoBus werden durchschnittlich 8 g CO_2 im Vergleich zur Nutzung des privaten Pkws gespart. Damit ergibt sich eine Einsparung von 1,12 kg für Ihre letzten zehn Fahrten und eine bessere Umweltbilanz für Sie.*

Besten Dank, dass Sie Teil der Pilotphase des EcoBusses sind und wie viele andere den EcoBus in der Harzregion nutzen. Wir freuen uns auf weitere Fahrten mit Ihnen.

Ihr EcoBus-Team.

*Diese Werte beruhen auf einer durchschnittlichen Auslastung von 1,56 Personen pro Fahrzeug. Die Schätzwerte ergeben sich durch die tatsächlich gefahrenen Kilometer des EcoBusses im Vergleich zu den direkten Fahrtstrecken vom Abhol- und Zielort (Daten von Anfang Oktober 2018). Die Bündelung von Fahrten wird bei der Berechnung berücksichtigt. Die durchschnittliche Fahrtstrecke wird als Referenzwert für die Summe der CO_2-Einsparungen genutzt. Als Vergleichswert für die Autonutzung dient eine CO_2-Belastung von 125 g pro Personenkilometer. Dieser Wert kann natürlich bei Ihrem PKW variieren.

(b) Example of a silver incentive (non-financial)

Gutscheincode: EBB2508EB02

Gutschein: Eine Doppelfahrt (Berg- und Talfahrt) mit der Kabinenbahn, inklusive Kaffee- und Kuchengedeck in der Bocksberghütte.
Einzulösen bis: 31.12.19

Der Gutschein ist nur gültig, wenn dieser ausgedruckt oder auf dem Handy vorgelegt wird.
Der Gutschein kann nur einmal eingelöst werden.

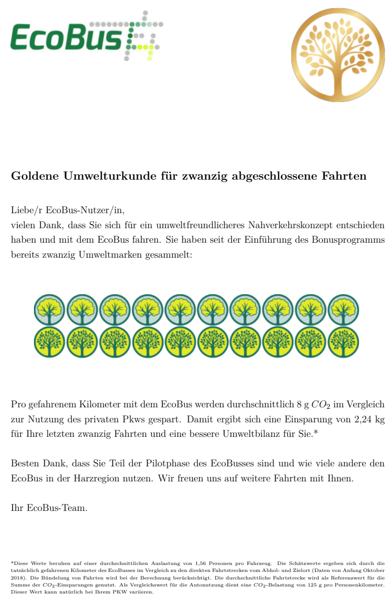
ErlebnisBocksBerg
Hahnenklee
Rathausstraße 6
38644 Goslar-Hahnenklee
www.erlebnisbocksberg.de
Telefon: 05325 - 2576

Mitte Dezember bis
Ende der Skisaison
(bis kein Skibetrieb mehr möglich ist):
täglich 9:00 Uhr - 16:30 Uhr
Ostern bis
Anfang November 2019:
täglich 9:00 Uhr - 18:00 Uhr

Anfang November bis
Mitte Dezember
sowie Ende der Skisaison bis
Ostern:
Geschlossen wegen Revision.

Witterungs- oder betriebsbedingte Änderungen sind jederzeit möglich und auf www.erlebnisbocksberg.de einsehbar.

(c) Example of a golden incentive (financial)



Goldene Umwelturkunde für zwanzig abgeschlossene Fahrten

Liebe/r EcoBus-Nutzer/in,
vielen Dank, dass Sie sich für ein umweltfreundlicheres Nahverkehrskonzept entschieden haben und mit dem EcoBus fahren. Sie haben seit der Einführung des Bonusprogramms bereits zwanzig Umweltmarken gesammelt:

Pro gefahrenem Kilometer mit dem EcoBus werden durchschnittlich 8 g CO_2 im Vergleich zur Nutzung des privaten Pkws gespart. Damit ergibt sich eine Einsparung von 2,24 kg für Ihre letzten zwanzig Fahrten und eine bessere Umweltbilanz für Sie.*

Besten Dank, dass Sie Teil der Pilotphase des EcoBusses sind und wie viele andere den EcoBus in der Harzregion nutzen. Wir freuen uns auf weitere Fahrten mit Ihnen.

Ihr EcoBus-Team.

*Diese Werte beruhen auf einer durchschnittlichen Auslastung von 1,56 Personen pro Fahrzeug. Die Schätzwerte ergeben sich durch die tatsächlich gefahrenen Kilometer des EcoBusses im Vergleich zu den direkten Fahrtstrecken vom Abhol- und Zielort (Daten von Anfang Oktober 2018). Die Bündelung von Fahrten wird bei der Berechnung berücksichtigt. Die durchschnittliche Fahrtstrecke wird als Referenzwert für die Summe der CO_2-Einsparungen genutzt. Als Vergleichswert für die Autonutzung dient eine CO_2-Belastung von 125 g pro Personenkilometer. Dieser Wert kann natürlich bei Ihrem PKW variieren.

(d) Example of a golden incentive (non-financial)

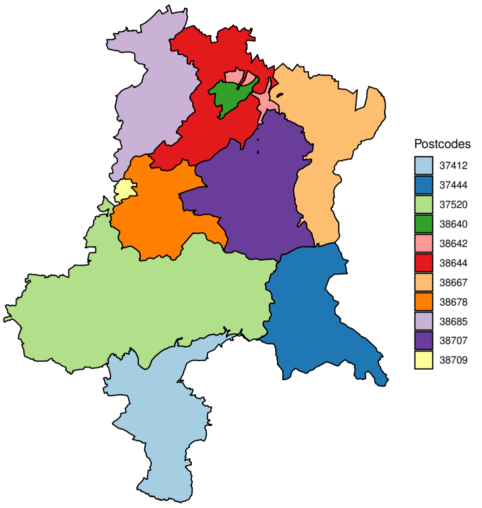
Figure C.2 Example of a financial silver incentive (a) and a non-financial silver incentive (b) and example of a financial golden incentive (c) and a non-financial golden incentive (d).

Appendix C.2

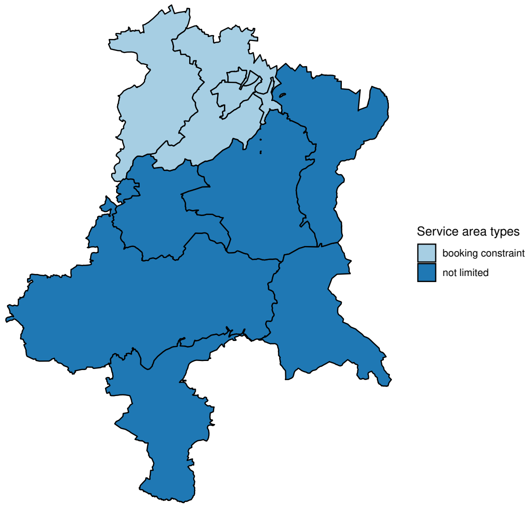
	financial incentive			non-financial incentive
	GlowGolf Harz	ErlebnisBockBerg	Aloha Aqualand	Environment certificate
Silver bonus	3D glasses	round trip (gondola lift)	Two hours sauna (2nd person)	information and confirmation on saved CO_2
Golden bonus	One free game (2nd person)	round trip (gondola lift) + pie + coffee	One day sauna (2nd person)	information and confirmation on saved CO_2
valid until (2019)	31st December	31st December	30th September	always
limited supply	no	no	500	no

Table C.1 Overview of the different incentives for the second EcoBus pilot phase.

Appendix D

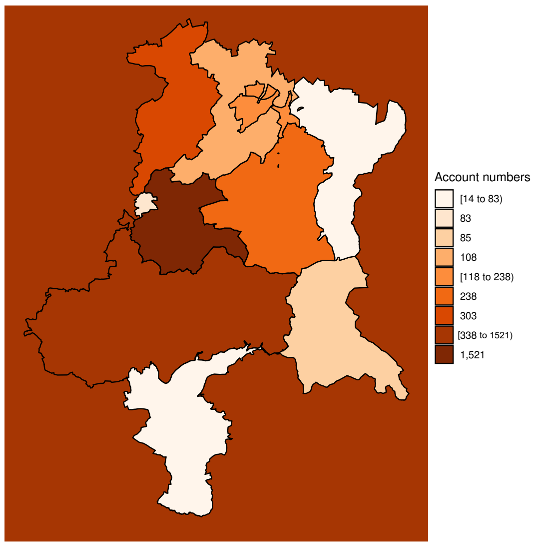


(a) Postcodes of the EcoBus service area



(b) Postcode areas with booking constraint

(c) Incentive types of the EcoBus service area



(d) Number of EcoBus accounts (November 2018)

Figure D.1 Overview of the postcodes (a) including the booking constraint (b), the incentive types (c) and number of Ecobus accounts (d). Source: Own representation, postcode shape files: Suche Postleitzahl team 2018.

Appendix E

The regression models are similar to the models in Section 5.2. The second 7 weeks of the pretreatment phase are pseudo treatments to detect a trend starting before the actual treatment.

Table E.1 Common trend assumption testing with control variables: Financial vs. Control (1) Non-Financial vs. Control (2)

	Dependent variable: weekly EcoBus journeys	
	(1)	(2)
pseudo treatment$_1$	0.010	0.028***
	(0.038)	(0.010)
pseudo treatment$_2$	−0.082**	0.008
	(0.039)	(0.028)
pseudo treatment$_3$	−0.045	−0.035**
	(0.059)	(0.016)
pseudo treatment$_4$	−0.163***	−0.011
	(0.045)	(0.031)
pseudo treatment$_5$	−0.008	0.008
	(0.043)	(0.029)
pseudo treatment$_6$	0.011	0.062
	(0.040)	(0.053)
pseudo treatment$_7$	0.030	0.046
	(0.045)	(0.032)
deleted journeys	0.083***	0.048**
	(0.016)	(0.021)
travel time	0.059***	0.047***
	(0.003)	(0.004)
waiting time	0.008**	0.005***
	(0.003)	(0.001)
additional passenger	0.179	0.118***
	(0.123)	(0.033)
active account	0.227***	0.101***
	(0.009)	(0.008)
Constant	0.010	0.006
	(0.011)	(0.007)
Observations	35,938	27,552
R^2	0.366	0.423
Adjusted R^2	0.366	0.422
Residual Std. Error	0.989	0.532
F Statistic	796.818***	773.069***
Note:	*p<0.1; **p<0.05; ***p<0.01; Standard errors in parentheses	

The regression functions are similar to the regressions in Section 5.3. The second 7 weeks of the pre-treatment phase are pseudo treatments to detect a trend starting before the actual treatment.

Table E.2 DiD Models: Common trend assumption testing with control variables: Financial vs. Non-Financial (1)

	Dependent variable: weekly EcoBus journeys
	(1)
pseudo $treatment_1$	−0.055*
	(0.028)
pseudo $treatment_2$	−0.075
	(0.071)
pseudo $treatment_3$	0.017
	(0.046)
pseudo $treatment_4$	−0.014
	(0.043)
pseudo $treatment_5$	0.041
	(0.054)
pseudo $treatment_6$	−0.020
	(0.092)
pseudo $treatment_7$	−0.018
	(0.071)
deleted journeys	0.037
	(0.023)
travel time	0.063***
	(0.006)
waiting time	0.010**
	(0.004)
additional passenger	0.202***
	(0.070)
active account	0.252***
	(0.016)
Constant	−0.015
	(0.027)
Observations	19,950
R^2	0.367
Adjusted R^2	0.367
Residual Std. Error	1.036
F Statistic	445.180***
Note:	*p<0.1; **p<0.05; ***p<0.01; Standard errors in parentheses

Appendix F

Table F.1 DiD Model: Financial vs. Control (1); Non-Financial vs. Control (2); matching based on driving characteristics of the passengers

	Dependent variable: weekly EcoBus journeys	
	(1)	(2)
treatment_1	0.079***	0.116***
	(0.013)	(0.012)
treatment_2	0.019	0.049***
	(0.014)	(0.008)
treatment_3	0.093***	0.148***
	(0.017)	(0.023)
treatment_4	0.153***	0.061***
	(0.012)	(0.017)
treatment_5	0.070*	0.132***
	(0.037)	(0.023)
treatment_6	0.033	0.050**
	(0.032)	(0.025)
treatment_7	−0.038**	−0.048*
	(0.017)	(0.025)
treatment_8	0.081***	−0.019
	(0.023)	(0.027)
treatment_9	0.043	0.066***
	(0.039)	(0.023)
treatment_{10}	0.100***	0.019
	(0.014)	(0.042)
treatment_{11}	0.062***	−0.029
	(0.015)	(0.035)
treatment_{12}	−0.055***	−0.054
	(0.021)	(0.036)
treatment_{13}	−0.033	0.113***
	(0.034)	(0.026)
treatment_{14}	−0.028	0.075***
	(0.022)	(0.022)
Constant	0.098***	0.130***
	(0.017)	(0.017)
Observations	71,876	55,104
R^2	0.009	0.010
Adjusted R^2	0.008	0.007
Residual Std. Error	0.809	0.659
F Statistic	6.601***	4.200***
Note:	*p<0.1; **p<0.05; ***p<0.01; Standard errors in parantheses	

Table F.2 DiD Models: Without Clausthal

	Dependent variable: weekly EcoBus journeys	
	DiD	DiD
	(1)	(2)
treatment_1	0.095	−0.008
	(0.092)	(0.073)
treatment_2	−0.002	−0.020
	(0.096)	(0.060)
treatment_3	−0.083	−0.108**
	(0.101)	(0.054)
treatment_4	−0.023	−0.052
	(0.050)	(0.069)
treatment_5	−0.092	0.018
	(0.089)	(0.079)
treatment_6	0.021	0.058***
	(0.075)	(0.022)
treatment_7	0.136	0.118***
	(0.085)	(0.027)
treatment_8	−0.017	0.018
	(0.120)	(0.036)
treatment_9	0.054	0.036
	(0.094)	(0.084)
treatment_{10}	0.032	0.102
	(0.129)	(0.088)
treatment_{11}	0.179**	0.212***
	(0.071)	(0.063)
treatment_{12}	0.107	0.203**
	(0.133)	(0.079)
treatment_{13}	0.125*	0.177***
	(0.074)	(0.042)
treatment_{14}	0.067	0.093*
	(0.053)	(0.054)
deleted journeys		0.047*
		(0.025)
travel time		0.050***
		(0.007)
waiting time		0.009***
		(0.001)
additional passenger		0.138**
		(0.063)
active account		0.243***
		(0.020)
certificate requested (silver)		1.304***
		(0.246)
certificate requested (golden)		1.631***
		(0.222)
voucher requested (silver)		0.705*
		(0.417)
voucher requested (golden)		3.104
		(1.889)
Constant	0.181***	0.016
	(0.062)	(0.025)
Observations	19,852	19,852
R^2	0.014	0.448
Adjusted R^2	0.012	0.447
Residual Std. Error	1.274	0.953
F Statistic	6.515***	315.033***
Note:	*p<0.1; **p<0.05; ***p<0.01; Standard errors in parentheses	

The models are similar to the regressions presented by Table 2. The only difference is that the analysis focuses on a sub sample without the data of Clausthal.

Appendix G

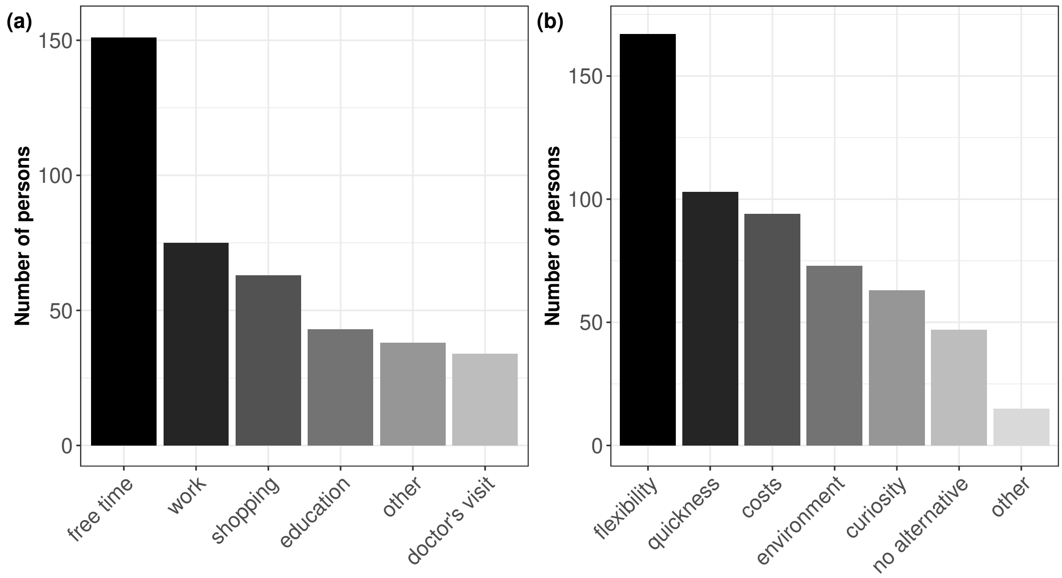


Figure I.1 The purpose (a) and reason (b) using the EcoBus; Observations=194.

Appendix H

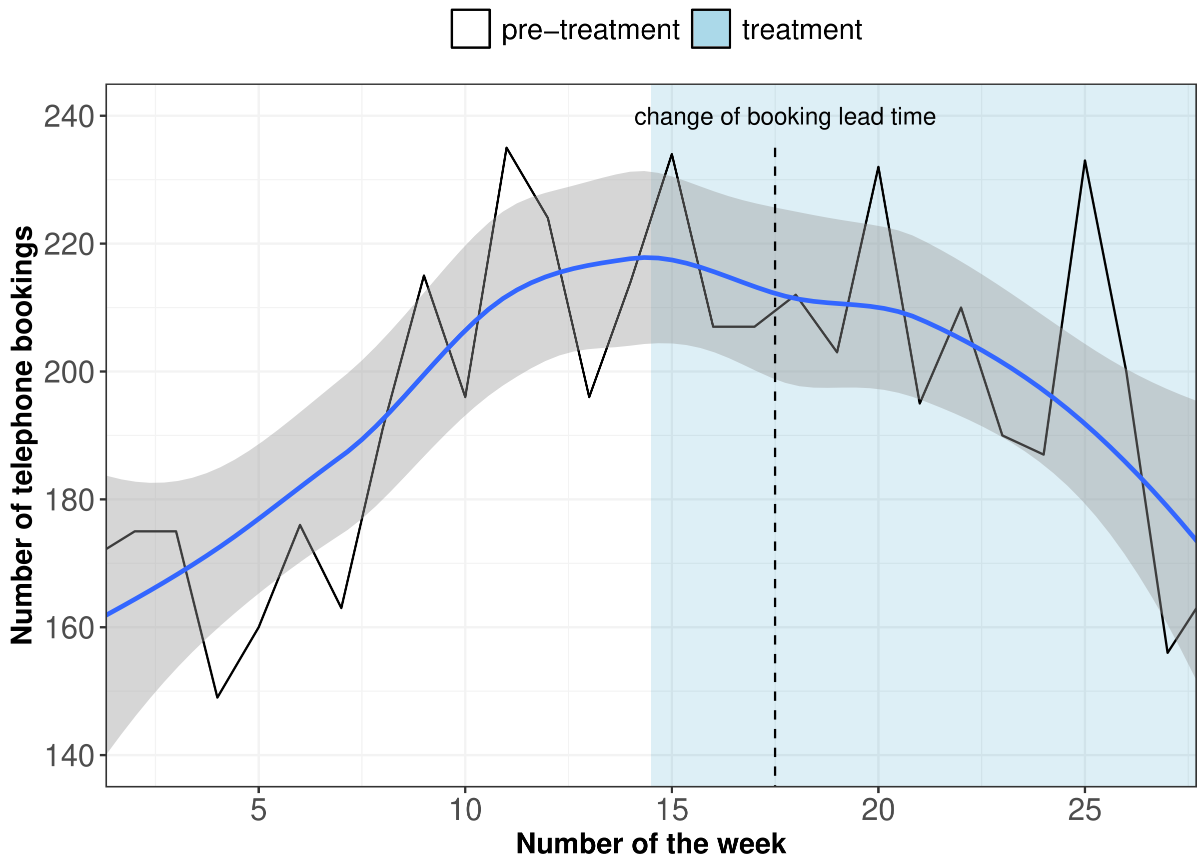


Figure J.1 EcoBus bookings via telephone over time.