The Long-Term Impact of Matching and Rebate Subsidies when Public Goods are Impure: Field Experimental Evidence from the Carbon Offsetting Market

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Abstract:
In this paper, we investigate both short- and long-term impacts of financial stimuli on public goods provision when contributions are tied to individual harm-related behavior. We conduct a large-scaled field experiment to examine voluntary contributions to a carbon offsetting program during the online purchase of a bus ticket. We systematically vary the individual payoff structure by introducing different matching grants (*1/3:1*, *1:1*, *3:1*) and price rebates (*r-25%*, *r-50%*, *r-75%*). Our results show that price rebates are more effective than matching schemes in raising participation rates while matching grants induce higher contributions to the offsetting program. We suspect differences in the personal responsibility for the compensated emissions to drive this result. Analyzing repeated bookings, we find decreasing treatment effects for returning customers except for the case of *1:1* matching grants. The equal matching scheme is also the only intervention that increases net contributions of customers compared to the control group.

Keywords: voluntary carbon offsets, randomized field experiment, public goods, rebate subsidy, matching subsidy

JEL: H41, C93, D03, L92

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1. Introduction

How can we stimulate voluntary contributions to public goods? So far, most experimental and empirical investigations have focused on the provision of pure public goods like donations to charities. Voluntary contributions to public goods are, however, increasingly attached to conventional private goods. Individuals therefore often take a joint decision on both the consumption of the private and the contribution to the public good. Typical examples include donations to providers of open-source software or green goods which explicitly tie public goods contributions to individual harm-related behavior.

As one of the most prominent green goods, carbon offsetting programs provide the opportunity to reduce pollution externalities and therefore mitigate own contributions to a public bad (Kotchen 2009). Recent empirical and experimental investigations confirm a positive relationship between the personal perception of individual impacts on climate change, e.g. for detrimental carbon emissions, and the willingness to contribute to climate protection (Löschel et al. 2013a, Diederich and Goeschl 2014). Individual contributions to a public good in the presence of own disamenities may therefore deviate from unrelated pure donations. In particular, it is unclear how financial stimuli such as price rebates or matching grants, having been shown to successfully enhance the provision of pure public goods (e.g., Karlan and List 2007, Meier 2007, Eckel and Grossman 2008), affect contributions in joint decisions on both goods.

In this paper, we examine repeated contributions to a public good that are explicitly tied to the harm-related consumption of a private good. We study carbon offsetting behavior in a large-scaled field experiment within the German long-distance bus market. Thereby, we systematically vary the individual payoff structure by introducing different financial stimuli in a randomized controlled trial. In particular, we offer different discounts by introducing either a price rebate on carbon offsets of 25% (*r-25%*), of 50% (*r-50%*) or 75% (*r-75%*). In addition, we consider different matching schemes that multiply contributions of the participants at a specific rate. We differentiate between matching rates of *1/3:1* (1/3 kg of CO_2 added for every kg offset by the customer), *1:1* and *3:1*. Our design therefore enables us both to compare the impact of these stimuli in contrast to the control group and to study how their intensity affects decision behavior. Moreover, using data on returning customers, we investigate the dynamic effects of the different stimuli, both while treatments were in place as well as for the time after treatment removal.

Previous field studies based on pure public goods like charitable giving decisions found both matching grants (Karlan and List 2007, Meier 2007) and price rebates (Eckel and Grossman 2008) to increase donations. In these studies, matching grants were more effective than rebates. Our analysis, based on a contribution decision being related to individual harm-related behavior and not based on a pure donation decision, delivers a more diverse picture: While all price rebate schemes increase participation rates in contrast to the baseline scenario, we find weaker effects for matching grants when focusing on first booking decisions. In terms of treatment intensity, we report modest price sensitivity with diminishing marginal effects for large interventions. In line with experimental findings from charitable donations by Karlan and List (2007), large match ratios (*3:1*) do not have any additional impact on participation rates, relative to smaller match ratios (*1:1*). Moreover, we also report similar results for rebates, where a rebate of 75% does not attract more customers than a 50% discount. In the dynamic analysis, we show that the effects of matching grants and price rebates on offsetting behavior decrease over time while they remain constant only for the equal (*1:1*) matching grants. This trend even persists after treatment removal, as *1:1* matching is the only treatment with long-term spill-overs. The equal matching scheme is also the only mechanism being able to significantly increase the net contributions of customers in contrast to the control group. Investigating the dynamics for repeated booking decisions suggests price rebates to rather serve as an instrument to advertise the carbon offsetting program among first customers, while *1:1* matching schemes appear to be more likely to stimulate the long-term involvement of returning customers.

The remainder of the paper is organized as follows. Section 2 provides an overview on the relevant literature and summarizes empirical findings from charitable giving experiments and other related studies. Section 3 provides a short introduction to the long-distance bus market and describes the experimental design. We present and discuss our results in section 4, before concluding in the last section.

2. Related Literature

So far, field experimental methods on public goods provision have mainly focused on charitable giving. They investigate the impact of different donation mechanisms and institutional settings, including challenge gifts, matching grants, price rebates and social information.

Karlan and List (2007) study the impact of matching grants on donation behavior based on mail solicitations to 50,000 prior donors of a nonprofit organization in the US. They report that matching increases both the probability to donate (+22%) and the revenue per solicitation (+19%) in contrast to the control group. Interestingly, their results suggest that larger match ratios (2:1 and 3:1) (in USD) do not have any additional impact on donation behavior in contrast to smaller matching rates (1:1). Rondeau and List (2008) investigate matching grants (1:1) in the presence of a threshold and a money-back guarantee in case the threshold is not reached. They do not find a significant difference between the matching treatment and a baseline scenario which may be due to the small sample size. Meier (2007) analyzes matching rates below 1:1 (1/4:1 and 1/2:1). The propensity to donate increases by six percentage points in the 50%-match while the effect of the 25%-match was smaller and not significant. Meier (2007) also provides the only long-run analyses of these interventions. He observes donors after the matching schemes were removed and finds negative effects for the year after the intervention and neutral effects when comparing matching and baseline over four points in time, including the time of intervention. Similar to our design, Eckel and Grossman (2008) set up a field experiment that allows the comparison of matching grants and price rebates. They use two pairs with identical relative price (1/4:1 vs. r-20% and 1/3:1 vs. r-25%) and report matching grants to lead to higher donations than price rebates. Anik et al. (2014) test a modified matching scheme for encouraging contributors to a charitable giving website to upgrade from single donations to recurring monthly donations. In addition to a standard 1:1 match, they consider a set of contingent matching rates informing donors that the charity will match (1:1) all donations made the same day but only if 25% (50%,75%) of all participants agree to upgrade. Their results suggest a 75%-contingent match to be most effective in terms of average individual donations and recurring donations (4.7% of all participants). A possible explanation for this finding is that a 75%-contingent matching scheme provides both social proof and a high likelihood that the threshold will be achieved.

The existing literature on charitable giving does not provide a comprehensive experimental design which simultaneously investigates both different rebate and matching schemes (below and above 1:1). Moreover, there is only little experimental evidence on long-term effects of matching schemes on donation behavior. Most importantly, none of these studies investigates the effect of price rebates on returning donators.

We are aware of only few field experimental investigations that address voluntary carbon offsets. To our knowledge, none of these studies considers rebates and matching schemes. Araña and León (2012) observe participation in a CO_2 offsetting program among air travelers to attend conventions and conferences in Gran Canaria during a time span of two years. They consider both different default settings (opt-in vs. opt-out) and offsetting prices (€10, €20, €40, €60). Based on 1,680 observations, the results suggest acceptance rates to decrease in prices irrespective of the frame of the default option. For small prices, participation is higher if the offsetting program is framed as willingness to withdraw from the program (opt-out) than as if it is modeled as a willingness to pay (WTP) for the program. The mean WTP for one ton of CO_2 corresponds to €39.82 in the opt-out frame and to €25.91 in the opt-in frame. Löfgren et al. (2012) conduct a similar experiment on CO_2 offsetting behavior among air travelling attendances at an environmental conference. While offsetting prices are fixed (€10 for participants from within Europe and €40 for those flying from outside Europe) they consider three different pre-default options (opt-in, opt-out, active choice). Highest participation rates were obtained in the active choice treatment (46.8%), followed by the opt-out (43.2%) and the opt-in treatments (39.3%) but no differences appeared to be significant in the sample. Compensation rates from flights within Europe (53.2%) are significantly higher than those from flights from outside Europe (24.4%). Based on these findings, they conclude that the effect of default options serving as nudges to affect decision behavior attenuates with market experience. Further survey-based investigations by Brouwer et al. (2008) among air travel passengers at Amsterdam Schiphol Airport indicate three quarters of all passengers to be willing to pay an additional carbon travel tax to the current price of the airplane ticket while acceptance rates are highest among European and lowest among Asian travelers.

A further strand of the related (framed) field experimental literature on public goods provision investigates acceptable cost levels and the willingness to pay to avoid negative consequences of climate change (Löschel et al. 2013a,b, Diederich and Goeschl 2014). However, in these experiments, subjects did not take part in a carbon offsetting program where contributions were explicitly tied to individual harm-related behavior. Instead, individuals faced the opportunity to purchase their desired amount of carbon allowances which were then withdrawn from the European Union Emissions Trading Scheme. These studies suggest that contribution decisions to public goods may vary if they are tied to harm-related behavior. This certainly depends on the individual perception of the underlying harmful behavior. Löschel et al. (2013a) report two third of their experimental subjects to believe that individual behavior influences climate change. In line with this finding, Diederich and Goeschl (2014) confirm a positive relationship between the perception of acknowledged lifestyle impacts on climate change and the willingness to pay for climate protection. Similarly, based on data from web interviews among driver's license holders from the U.S and Germany, Lange and Ziegler (2012) find agents with a higher feeling of responsibility for carbon emissions to be more likely to state their willingness to pay for voluntary carbon offsets. There is only limited data available on participation rates in offsetting programs being regularly in place. Take-up rates in the aviation sector are, however, expected to be rather in the single digits (Greenair 2011).[1]

3. The field experiment

3.1. The offsetting program

In January 2013, Germany lifted its ban on long-distance bus operations. An amendment to the German Passenger Transportation Act (Personenbeförderungsgesetz, PBefG) ended the existing interdiction of additional scheduled national transport services if a corresponding railway service was already established (e.g., BMVIT 2013).[2] Since the deregulation in 2013, the long-distance bus market has been expanded rapidly. About 40 bus companies are currently operating on the highly fragmented market (IGES 2013). By the end of 2013, weekly scheduled national trips have tripled compared to the beginning of the year. Within the same time period, bus operators established 76 additional regular routes (+123%). Similarly, transport volume increased by 12.5% to 1.3 million passengers within the first half of 2013 compared to 2012, while passenger railway transport decreased by 1.2% to 63 million (DESTATIS 2013).

For conducting our field experiment, we collaborated with one of the pioneering bus operators that entered the market in January 2013. The company did not offer or participate in any carbon offsetting program before the experiment was launched in October 2013. We introduced the program without any advertising or pre-announcement. It was designed to be a part of the usual online booking system at the company's official website. The booking system allows buying either one-way or return tickets, for up to four passengers at a time. After passengers had chosen their individual trips, the possibility to offset carbon emissions was offered in neutral words, including price and amount (in kilograms of CO_2) of the compensation.

Based on individual carbon emissions of 47g CO_2 per passenger kilometer[3] and a price of 17.90 € per ton CO_2 charged by the collaborating offsetting provider, offsets were sold at 8 cents (in €) per 100 passenger kilometer. Passengers were required to make a binary choice by clicking either "yes" or "no". They also had the opportunity to obtain detailed information on

[1] Quantas (2010) reports that 7.5% to 9% of their online customers offset their carbon emissions in 2009/2010 resulting in a total volume of 240,000 tons of CO_2.
[2] The ban dated back to 1935 and was initially introduced to ensure profitability of public railway passenger services due to high investment costs for railway infrastructure. Note that the liberalization only covers the long-distance market.
[3] Carbon emissions include both direct carbon emissions from fuel consumption (39g CO_2/km) and the life-cycle-assessment for the vehicle based on the GEMIS database (IINAS 2013).

the offsetting program on request. Therefore, we are able to detect whether learning about the specific offsetting project is associated with differences in offsetting behavior.[4] After making their decision, passengers received a list of the items they intended to buy (including their offsetting expenses), were asked to give personal information (no additional information beyond the usual booking process was asked) and to enter payment details.

Questionnaire data collected after the experiment suggest the vast majority of passengers to be between 16 and 35 years old and most of them to have an academic background. Men and women are equally represented.[5]

3.2. Experimental design and procedure

We introduced different interventions to the offsetting program in three subsequent stages (see Figure A1). In stage 1, which also coincided with the introduction of the carbon offsetting program, we varied informational settings holding relative prices and amounts constant. In stage 2, matching grants and price rebates were introduced holding the informational setting constant. Finally, in stage 3 we reproduced the conditions from stage 1 with the aim to study decision behavior over time. After the end of stage 3, the offsetting program continued to exist in a fixed setting. In this paper, we focus on the interventions in stage 2.

To study the effects of price rebates and matching schemes on offsetting behavior, we ran a baseline condition and six treatments where we varied the incentives keeping wording and the general framework as similar as possible. Both types of subsidies were communicated as a temporal offer given by the bus company to support individual offsetting contributions: rebates directly reduced the passenger's offsetting price while matching grants resulted in additional carbon offsets being paid by the company (see translated screenshots in Figure A2). In particular, we considered three levels of price rebates reducing the costs for offsets by 25%, 50% and 75% (*r-25%*, *r-50%*, *r-75%*), and equivalent matching grants (*1/3:1*, *1:1*, *3:1*).
It should be noted that the price per unit CO_2 is identical in *r-50%* and *1:1* (8.95 €/t CO_2) while the amount of CO_2 covered in *1:1* is twice as high as in *r-50%*. Similar considerations hold for *r-25%* and *1/3:1* (13.45 €/t CO_2), and *r-75%* and *3:1* (4.50 €/t CO_2) respectively. In contrast to many experimental settings on charitable donations, in our experiment individuals

[4] Those interested were informed that contributions were used to support an energy efficiency project in the public sector dealing with improved household charcoal stoves in Accra/Ghana and that greenhouse gas emissions reductions within this project were certified under a voluntary certification process (VER) and labelled as a Gold Standard project that is considered to be the most rigorous international certification benchmark for quality and compliance of carbon offsetting programs (see http://www.goldstandard.org/ for more information, access on January 10, 2014).

[5] Questionnaires were distributed both in the bus of the collaborating operator, during randomly determined bus rides, and online, using the operator's email list of customers, yielding 403 observations.

did not have the opportunity to adjust their contribution levels independently but had a binary choice. Emission quantities were derived from the underlying trip and individuals did not have the possibility to independently determine their own contribution given the respective rebate or matching scheme. The total amount of CO_2 that can be offset is therefore always higher in the matching treatments than in the price rebate schemes. The effect of price rebates and matching schemes with the same price per unit CO_2 are therefore not assumed to be equivalent in our case.

Treatments assignment was based on a randomly generated number that was saved as a browser cookie (ID) on the individuals' computers when entering the website for the first time. If individuals interrupted the booking process, returned to the website later and the cookie was not deleted, they remained within the same treatment. This randomization strategy allows us to investigate repeated bookings of returning customers during the entire experiment.[6]

4. Experimental results

We recorded 11,258 bookings in seven conditions, including both single- and multi-trip bookings.[7] For the analysis in the paper, we exclude IDs that had been already faced with an offsetting decision in phase 1 (5.2%). Our results are therefore based on 10,623 booking decisions.

Observations are fairly equally distributed across treatments with about 1,500 observations in each setting (see Table 1 for an overview). The mean travel distance is 274 km resulting in individual CO_2 emissions of 12.9 kg per booking. Travelers face an average hypothetical offsetting price of 0.23 € which accounts for about 1.0% of the average total ticket price per booking.

Throughout the experiment we observe multiple bookings for about a quarter of all participants. We start our analysis by focusing on the first booking per ID (sections 4.1 - 4.3) and then extend the discussion to all bookings to study long-term effects (section 4.4). As offsets are offered in different combinations of prices and quantities, we study effects on both participation rates and on contribution levels.

[6] If the individual browser settings had cleared cookies in the meanwhile individuals were randomly reassigned.

[7] In about 36% of all bookings more than one trip is purchased leading to a higher number of trips than bookings in the aggregate.

Table 1: Summary statistics of the experimental design (per booking)

Treatment	*control*	*1:1*	*r-50%*	*3:1*	*r-75%*	*1/3:1*	*r-25%*	all
bookings per ID	1.4	1.3	1.4	1.3	1.4	1.4	1.3	1.4
distance (km)	267.8	276.4	274.7	273.6	276.1	270.6	278.2	273.9
CO_2 (kg)	12.6	13.0	12.9	12.9	13.0	12.7	13.1	12.9
CO_2 per trip (kg)	8.7	8.7	8.8	8.7	8.8	8.7	8.7	8.7
totalCO_2 per trip (incl. matches, kg)	8.7	17.5	8.8	34.7	8.8	11.5	8.7	14.2
ticketprice (excl. offsetting cost, €)	18.3	18.8	18.4	18.7	18.6	18.3	18.7	18.5
relative price (% of total booking)	1.3	1.3	0.6	1.3	0.3	1.3	1.0	1.0
voucher (%)	1.9	2.3	2.6	2.4	2.4	1.7	1.5	2.1
info button request (%)	2.3	0.9	1.6	1.2	1.6	1.3	1.4	1.5
return ticket (%)	28.6	30.4	29.8	30.6	30.7	29.3	32.0	30.2
group ticket (%)	9.7	9.4	9.5	9.1	10.6	9.2	9.5	9.6
female (%)	52.8	53.5	53.9	50.7	53.9	56.3	53.4	53.5
carbon price (€/t CO_2)	17.9	8.95	8.95	4.5	4.5	13.45	13.45	10.26
Observations	1,542	1,463	1,522	1,557	1,496	1,557	1,486	10,623

4.1. Participation

In this section, we analyze treatment effects with respect to the probability of taking part in the offsetting program, measured as the binary variable *participation*. The average participation rate for first bookers is 30.8% (Table 2). Take-up rates in the different rebate conditions amount to 30.6% (*r-25%),* 35.7% (*r-50%),* and 36.2% (*r-75%*) while they are 26.2% (*1/3:1),* 30.8% (*1:1)* and 29.1% (*3:1*) in the matching schemes. Except for *1/3:1* matching, participation in all treatments is higher than in the control group (27.0%) (see also

Figure A3).

To further investigate these first observations, we apply a series of binary logit models and non-parametric Mann–Whitney U (MW-U) tests. The discussion throughout the paper is primarily based on the regression results. We refer to the MW-U tests (provided in the Appendix) only in cases where differences between the two statistical measures appear. We include both treatment indicators and a set of additional control variables in different model specifications. In this section, we focus on treatment effects only, providing a more detailed discussion on the controls and their impact on take-up in section 4.3.

Table 2: Summary statistics of the experimental results

Only first booking								
Treatment	*control*	*1:1*	*r-50%*	*3:1*	*r-75%*	*1/3:1*	*r-25%*	All
compensated bookings (%)	27.0	30.8	35.7	29.1	36.2	26.2	30.6	30.8
resulting compensation :								
- without match (kg CO_2)	3.4	3.9	4.5	3.6	4.7	3.3	3.9	3.9
- including match (kg CO_2)	3.4	7.8	4.5	14.4	4.7	4.4	3.9	6.2
offsetting payments								
- total payments (€ cents)	6.0	13.8	8.0	25.6	8.4	7.7	7.0	11.0
- by customers (€ cents)	6.0	6.9	4.0	6.4	2.1	5.8	5.2	5.2
Observations	1,317	1,243	1,295	1,316	1,270	1,307	1,276	9,024
All bookings								
Treatment	*control*	*1:1*	*r-50%*	*3:1*	*r-75%*	*1/3:1*	*r-25%*	All
compensated bookings (%)	26.8	31.4	34.0	28.3	34.6	26.1	29.9	30.1
resulting compensation:								
- without match (kg CO_2)	3.3	3.9	4.2	3.5	4.5	3.2	3.8	3.8
- including match (kg CO_2)	3.3	7.8	4.2	13.9	4.5	4.3	3.8	6.0
offsetting payments								
- total payment (€ cents)	5.9	13.8	7.5	24.7	7.9	7.7	6.7	10.6
- by customers (€ cents)	5.9	6.9	3.7	6.2	2.0	5.8	5.0	5.1
Observations	1,542	1,463	1,522	1,557	1,496	1,557	1,486	10,623

The regression results widely confirm our descriptive observations (Table 3). All model specifications indicate a positive effect of all price rebate schemes on participation in contrast to the control group (*r-25%*: $p < 0.05$, *r-50* and *r-75%*: $p < 0.01$). Behavioral responses to matching grants again remain rather modest. Only *1:1* matching appears to be clearly effective enhancing participation across the different model specifications (at least $p < 0.05$). The coefficient for the weaker matching intervention *1/3:1* is even negative but does not differ significantly from zero. The effect of *3:1* matching is positive but slightly off conventional levels of significance ($0.10 < p < 0.15$). A potential driver of the missing significance might be the higher total amounts of CO_2 in the *3:1* treatment. When controlling for total kg of CO_2 including the matched quantities in models (5) and (6) in Table 3, we indeed do find a significant effect of the highest matching scheme.[8]

[8] The correlation between *3:1* and *totalCO2* is 0.56. Hence, we should not expect biased results due to multicollinearity. Nevertheless we are aware that this estimate might slightly overestimate the effect of *3:1* matching. Figure A5 plots the predicted offsetting probabilities over the amount of CO_2, both including and excluding matches, and thus visualizes the different sizes of the estimated treatment effects.

Table 3: Maximum likelihood estimates in binary logit models, treatment effects and determinants on offsetting behavior, only first booking, dependent variable: participation

Explanatory variables	(1)	(2)	(3)	(4)	(5)
r-25%	0.172**	0.201**	0.198**	0.193**	0.191**
	(0.0869)	(0.0882)	(0.0882)	(0.0883)	(0.0882)
r-50%	0.404***	0.431***	0.431***	0.427***	0.424***
	(0.0849)	(0.0861)	(0.0861)	(0.0861)	(0.0860)
r-75%	0.427***	0.462***	0.462***	0.455***	0.452***
	(0.0852)	(0.0865)	(0.0865)	(0.0865)	(0.0865)
1/3:1	-0.0443	-0.0187	-0.0206	-0.0208	-0.00685
	(0.0884)	(0.0894)	(0.0894)	(0.0894)	(0.0902)
1:1	0.184**	0.225**	0.222**	0.222**	0.264***
	(0.0873)	(0.0881)	(0.0881)	(0.0881)	(0.0959)
3:1	0.103	0.134	0.130	0.130	0.257*
	(0.0868)	(0.0878)	(0.0878)	(0.0878)	(0.140)
CO_2		-0.00837***			
		(0.00266)			
CO_2 per trip			-0.0171**	-0.0165*	
			(0.00844)	(0.00844)	
return ticket			0.0144	0.0151	0.00983
			(0.0504)	(0.0504)	(0.0503)
group ticket			-0.262***	-0.261***	-0.263***
			-0.0171**	-0.0165*	(0.0821)
relative price				-0.710***	-0.801***
				(0.217)	(0.303)
total CO_2 per trip					-0.00488
					(0.00428)
voucher		-0.248	-0.245	-0.262	-0.263
		(0.175)	(0.175)	(0.176)	(0.176)
info		1.890***	1.879***	1.879***	1.876***
		(0.185)	(0.184)	(0.184)	(0.184)
female		-0.0865*	-0.0906*	-0.0896*	-0.0905*
		(0.0462)	(0.0463)	(0.0463)	(0.0463)
constant	-0.993***	-0.897***	-0.832***	-0.828***	-0.926***
	(0.0620)	(0.0747)	(0.0989)	(0.0989)	(0.0778)
log likelihood	-5541.77	-5474.85	-5472.36	-5471.18	-5472.44
observations	9,024	9,024	9,024	9,024	9,024

Note: Omitted treatment category is *control*, robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Postestimation Wald tests on selected explanatory variables after binary logit regression on participation decision, column (4)

Coefficient	r-50%	r-75%	1/3:1	1:1	3:1
r-25%	<***	<***	>**	<	<
r-50%		<	>***	>**	>***
r-75%			>***	>***	>***
1/3:1				<***	<*
1:1					<

Note: We compare rows with columns. *** $p<0.01$, ** $p<0.05$, * $p<0.1$, We test whether the difference of two estimated coefficients is significantly different from zero, e.q. we test whether b[r-25%] = b[r-50%].

We compute average marginal and discrete probability effects to get an impression on the magnitude of the estimated treatment effects (Table A3). Point estimates of the first booking suggest price rebates to increase the propensity to take part in the offsetting campaign in the first booking by 4.0 percentage points for *r-25%*, 8.9 for *r-50%* and 9.5 for *r-75%*. Confidence intervals (reported at 95%-significance levels) for the 50% and 75% price reduction cover similar ranges (5.4 to 12.4 percentage points for *r-50%* and 6.0 to 13.0 percentage points for *r-75%*). That is, additional effects of a three-quarter price rebate in contrast to a 50% price rebate remain rather modest. Moreover, *1:1* matching grants increase the propensity to contribute by 4.6 percentage points (95% conf. interval: 1.0 to 8.2 percentage points). We summarize these first findings and obtain our first result:

Result 1

Price reductions of 25% or more and a 1:1 matching scheme increase the share of passengers that offset their CO_2 emissions in the first booking decision. Controlling for the fact that matching schemes always require participants to purchase higher quantities further also reveals a positive effect of 3:1 matching on participation.

In a next step, we are interested to what extent the intensity of the intervention affects decision behavior. For the case of matching rates, equal shares (*1:1*) lead to more offsetting than smaller matches (*1/3:1*, $p < 0.01$, Table 4) while, similar to the findings of Karlan and List (2007), large matching rates (*3:1*) do not have any additional impact compared to *1:1*. Similarly, price rebates of 50% and 75% lead to higher participation rates compared to a rebate of 25% ($p < 0.01$, Table 4). A three-quarter price rebate, however, does not yield any additional effect compared to *r-50%*. Hence, the results of Karlan and List (2007) seem to generalize to price rebates. We formulate the following result that complements our previous findings:

Result 2

Both in price rebates and matching schemes, an equal split of contributions between passenger and bus company (1:1 or r-50%) leads to higher participation rates than a weaker intervention (1/3:1 or r-25%) and is statistically equivalent to a stronger intervention (3:1 or r-75%).

Third, our design enables us to compare price rebates and matching grants with the same price per unit CO_2 of giving (e.g., *1:1* vs. *r-50%*). Offsetting behavior clearly differs between the two types of interventions. Within pairs, price rebates always lead to higher participation rates than matching grants (*1:1* vs. *r-50%*: $p < 0.05$, *1/3:1* vs. *r-25%*: $p < 0.1$, *3:1* vs. *r-75%*: $p < 0.01$, Table 4). This result is in stark contrast to previous evidence from a pure public good context. Of course, we are aware that our design embeds further aspects that may limit the comparability of the two classes of interventions. In particular, passengers were not able to adjust offsetting quantities but faced a binary choice in our experimental setting. The comparison of price rebates and matching grants thus involves different quantity levels (see Table 2). To mitigate this difference between treatments we control for total amounts of CO_2 (including the matched kilograms). However, even then, the smaller effect size of matches persists (see Table 3, model (5)). This provides evidence that decision behavior in our setting differs more fundamentally from a pure public goods context. We suggest that the degree of responsibility for the emissions that are being offset may explain our results. In rebate schemes, participants always decide upon offsets equivalent to the emissions caused by their specific trip. In contrast, in the matching schemes the benefits compared to the baseline setting are given by additional offsets unrelated to the current trip. In particular, in the *3:1* scheme, the unrelated offsets even outweigh the related ones. To further explore this idea, we run an additional set of regressions controlling for the resulting unit price (€/tCO_2) and the share of offsets exceeding own emissions instead of treatment dummies. We find smaller shares of participation for matches than for price rebates. Moreover, we report a lower propensity to offset as the share of unrelated emissions increases (see Table A5). Despite the inherent limitations of the analysis, our results suggest that the willingness to offset emissions beyond the related environmental harmful behavior remains rather modest. This might hamper the effectivity of matching schemes in this context, in particular for large matching rates.

Result 3

Passengers are less likely to compensate as the share of offsets unrelated to their trip increases.

4.2. Contributions

Next, we turn to resulting contribution levels. Except for *1/3:1*, total average offsetting payments (including matches) are higher in all treatments than in the control group (see Table 2), being highest in *3:1* matching. These differences are also significant (see Table 5) and show that all but the 1/3:1 scheme reach the goal of increasing the share of carbon neutral transportation services. Our main interest, however, lies in the contributions by the customers net of subsidies, as the company could increase offsets at own costs in the absence of incentive schemes.[9] Averaged over all first booking decisions, net contributions amount to 5.2 cents (in €) per booking (Table 2 and Figure A4). In the rebate conditions, passengers

[9] Note that a true efficiency analysis would require capturing all costs and benefits that arise from implementing the different schemes. For simplicity we assume these to be zero and constant across schemes.

contribute 5.2 cents (*r-25%)*, 4.0 cents (*r-50%)*, and 2.1 cents (*r-75%*) and thus less than in the control group (6.0 cents). Contributions in the matching schemes amount to 5.8 cents (*1/3:1)*, 6.9 cents (*1:1)*, and 6.4 cents (*3:1*). Hence, only the *1:1* and the *3:1* matching scheme induce customers to contribute more than in a control setting. We conduct a series of Tobit regressions to further investigate these differences (Table 5). The results of a MW-U test are reported in the Appendix (Table A2). In this subsection, again, we only focus on treatment effects and provide a more detailed discussion on the controls in section 4.3. The regression results confirm the superiority of the *1:1* matching scheme ($p < 0.05$, Table 5, columns 4-6) which is also the only scheme inducing significantly higher net contributions than in the control group. Moreover, there is statistical evidence that net contributions averaged over all customers are lower in *r-75%* than in the control group ($p < 0.1$, Table 5, columns 4-6). This effect is intuitive as equalizing net contributions in *r-75%* compared to the control group would require participation rates to quadruple. Given our results from the previous section, we know that participation rates only rise modestly and are far from reaching 100% in *r-75%*. Summarizing these observations, we obtain the following result:

Result 4

1:1 matching is the only incentive scheme effectively increasing customers' net contributions in contrast to the baseline scenario.

We now consider the effect of the intensity of the treatments on net contributions. A price rebate of 75% significantly decreases net contribution levels in contrast to smaller interventions (*r-25%*: $p < 0.05$, *r-50%*: $p < 0.01$, Table 6). The difference between *r-25%* and *r-50%* is not significant in our sample. In line with the observations on participation rates, a *1:1* match leads to higher net contribution than the weaker intervention ($p < 0.01$) and is statistically equivalent to the *3:1* match. Pairwise comparisons between matches and rebates reveal that the latter lead to lower average contribution levels (see also Figure A4). Based on Tobit regressions, differences become significant for medium (*r-50%* vs. *1:1, $p < 0.05$*) and high (*r-75%* and *3:1, $p < 0.01$*) interventions (see Table 6) confirming the superiority of matching rates in raising contribution levels (e.g., Eckel and Grossman 2008).

Table 5: Maximum likelihood estimates in Tobit models, treatment effects and determinants of offsetting behavior, only first booking, dependent variable: payments

Explanatory variables	payment_tot (1)	payment_tot (2)	payment_tot (3)	payment_pass (4)	payment _pass (5)	payment _pass (6)
r-25%	5.171**	5.322**	5.267**	0.245	0.264	0.237
	(2.522)	(2.433)	(2.443)	(1.325)	(1.262)	(1.267)
r-50%	11.42***	11.43***	11.41***	0.437	0.384	0.376
	(2.444)	(2.347)	(2.357)	(1.227)	(1.168)	(1.172)
r-75%	12.50***	12.46***	12.29***	-2.132*	-2.225**	-2.309**
	(2.463)	(2.359)	(2.374)	(1.185)	(1.133)	(1.139)
1/3:1	1.962	2.567	2.557	-0.673	-0.417	-0.420
	(2.640)	(2.543)	(2.542)	(1.394)	(1.328)	(1.327)
1:1	15.79***	16.55***	16.64***	2.828**	3.123**	3.164**
	(2.837)	(2.688)	(2.730)	(1.415)	(1.330)	(1.349)
3:1	31.42***	32.05***	32.07***	1.425	1.673	1.675
	(3.272)	(3.147)	(3.152)	(1.365)	(1.301)	(1.300)
CO_2		0.850***			0.416***	
		(0.148)			(0.0701)	
CO_2 per trip			1.369***			0.677***
			(0.291)			(0.134)
return ticket			12.97***			6.271***
			(1.671)			(0.747)
group ticket			7.665**			3.795***
			(3.153)			(1.416)
relative price			-8.164***			-3.702***
			(1.289)			(0.569)
voucher		-4.230	-5.050		-1.545	-1.932
		(5.794)	(5.856)		(2.554)	(2.594)
info		53.36***	53.84***		24.11***	24.35***
		(5.812)	(6.457)		(2.311)	(2.654)
female		-2.423*	-2.708*		-1.178*	-1.314**
		(1.448)	(1.455)		(0.649)	(0.653)
Constant	-41.38***	-50.71***	-61.87***	-13.46***	-17.86***	-23.50***
	(2.547)	(3.475)	(5.823)	(1.169)	(1.543)	(2.630)
Log Likelihood	-18264.7	-18139.3	-18138.1	-16221.8	-15975.6	-15975.0
Observations	9,024	9,024	9,024	9,024	9,024	9,024

Note: Omitted treatment category is *control*, robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Postestimation Wald tests on selected explanatory variables after Tobit regression on compensation levels, column (6)

Coefficient	r-50%	r-75%	1/3:1	1:1	3:1
r-25%	<	>**	>	<**	<
r-50%		>***	>	<**	<
r-75%			>*	<*	<***
1/3:1				<***	<
1:1					>

Note: We compare rows with columns. *** $p<0.01$, ** $p<0.05$, * $p<0.1$, We test whether the difference of two estimated coefficients is significantly different from zero, e.g. we test whether b[r-25%] = b[r-50%].

Intuitively, this result is also in line with a certain inelasticity of demand with respect to prices. Rebates affect both the payments made by the customer and the customer's demand. Based on our data, the first effect dominates the latter, leading to smaller contribution levels – both compared to matching schemes and baseline. Put differently, the increase in participation in the different rebate schemes is not able to compensate the lower average contribution levels for each individual that decides to contribute. We summarize these findings by the following result:

Result 5

Pairwise comparisons between rebates and matches reveal that matches lead to higher contribution levels. The comparative advantage increases in size and significance as the intervention becomes stronger.

4.3. Further determinants of behavior

In this section, we analyze the impact of further explanatory variables on decision behavior. As a single booking process may contain several trips we control for the "size" of the booking in different ways. In the simplest approach we simply include the total amount of CO_2 emissions attributed to the booking in (CO_2). In a next step, we decompose this value into its underlying factors: the length of the single leg trip, captured by the corresponding emission level (*CO_2 per trip*), whether the journey was booked as a return trip (*return ticket*) and whether tickets were bought for more than one traveler (*group ticket*). All three components are hardly correlated and thus allow us to perform a decomposition of the effect of CO_2. We also look at the share of compensation costs with respect to the total price of the booking (*relative price*) and at the amount of CO_2 per trip including the match (*totalCO_2 per trip*). Further controls include *voucher*, equaling one if an individual redeemed a coupon leading to a cost reduction of the trip, and the indicator variable *info* which equals one if customers click on the 'Info button' to get more detailed information on the offsetting activity. Interestingly, only a small minority of customers (about 1.5%) make use of this possibility to learn more about the offsetting activity, the quality labels and the project where contributions are collected for suggesting little interest in this kind of information during the first booking. Given the small share of customers learning about the underlying project we are confident that we measure the demand for carbon offsets and not the customers' support for a specific project. Based on the dummy variable *female* we control for potential differences between men and women. We provide descriptive information on explanatory variables in Table 1.

Our regression results suggest the *CO_2 per trip* and *group tickets* reduce responsiveness to the interventions while it is irrelevant whether the *return ticket* was booked or not (Table 3 and Table 5). That is, the propensity to contribute significantly decreases if individuals purchase a ticket not only for a single person (presumably the buyer) but requires decisions for other persons that are not necessarily present when the ticket is purchased. This finding is in line with experimental evidence from a dictator game with an environmental organization (the WWF) (Carlsson et al. 2011). Average donation decreases in a scheme where the decision of the dictator on contribution levels applies to all group members. Estimating average marginal effects suggest the propensity to contribute to the carbon offsetting program for groups to be 5.4 percentage points lower than for single bookings ($p < 0.01$, Table A3).

Averaged over all treatments, *female* customers make less use of the offsetting program than men, both in terms of participation rates and contribution levels. The point estimate of the average marginal effect of being female amounts to 1.9 percentage points with respect to participation ($p < 0.05$, Table A3) and to 1.3 Euro cents with respect to contribution levels ($p < 0.05$, Table A4). Does this mean that women are less likely to contribute in this context? This would be a clear contradiction to the literature that finds women to donate significantly more than men in charitable giving experiments (e.g., Eckel et al. 2007, Li et al. 2011). We apply a more detailed analysis on interaction to study gender effects. First, we interact the female dummy with a dummy that is one for the control condition and zero in all subsidy treatments (*female X control*) and find that the negative effect only holds for the subsidy treatments, while the estimate is even positive for the control setting (Table A6, columns (1) and (4)). Hence, there is no negative baseline effect for females but rather a reduction of the treatment effects. Next, we split the sample in male and female bookers and report smaller treatment effects for female bookers compared to men (Table A6, columns (2), (3), (5) and (6)). In particular, we do not find any significant effect of matching schemes for women.[10]

Our results add to the mixed evidence on gender effects in this context. Previous experimental findings on carbon offsets report gender neutrality (Löfgren et al. 2012, Diederich and Goeschl 2014, Blasch and Farsi 2014), rather positive effects for men (Löschel et al. 2013b) or positive effects for women (MacKerron et al. 2009). Gender specific treatment effects of matching schemes, however, have to our knowledge not been reported in the literature yet and deserve further investigation. They are, to some extent, related to the findings of Karlan and List (2007), who pointed out that matching schemes only worked in states where the Bush administration was supported in a hitherto election. In Karlan and List, the target of contributions was a liberal political institution, suggesting that in particular those typically not inclined to donate are stimulated by the financial incentives. A similar story might hold in our case as men, donating weakly less than women in baseline, react strongest in the presence of stimuli (Table A6). These findings are also in line with Andreoni and Vesterlund (2001) who

[10] Adding interaction terms of treatment effects and the gender dummy in the regressions in Table 3 support this finding.

find that women are more generous than men when it is relatively expensive to give, while men begin to give more than women as the price of giving decreases. Their findings for prize manipulations seem to generalize to subsidy schemes.

Clicking on the *info* button is positively correlated with stronger participation in the offsetting program. Given the small share of people actually using his option and the potential for self-selection we do not interpret this finding as a causal relationship. Summarizing the most important factors from the regression analysis beyond treatment effects yields our next observation:

Result 6

Group purchases, longer travel distances and high costs relative to the actual ticket price reduce the likelihood to take part in the carbon offsetting program. Women are less responsive to the incentive schemes than men.

4.4. Long-term effects

We use the full sample of bookings, including repeated bookings, to explore potential long-term effects of the different treatments. It is important to point out that due to our randomization procedure repeated customers were reassigned to the same treatment. Hence, we can measure the individual number of repeated bookings of the same passenger (*recurrences*), indicating the number of times the individual has been exposed to the treatment.[11]

In a first step, we add recurrences (Table 7 and Table 8) to capture a general trend for repeated bookers. A key insight is that point estimates for marginal effects of the treatments are smaller in size (and significance) than in the analysis of first bookings Table A7 and Table A8). Moreover, the variable recurrences has a negative and significant coefficient in all model specifications ($p < 0.05$, Table 7), showing that the propensity to offset emissions is decreasing in the number of bookings made by the same ID. This observation is in line with the findings of Allcott and Rogers (2014) on long-term impacts of behavioral interventions and may raise concerns on the effects of these contribution schemes for returning customers. As shown in Table A7, for each additional booking process (per ID) the probability to contribute decreases on average by 2.3 percentage points.

[11] We also investigated the effect of treatment assignment on recurrences but the differences do not appear to be significant in our sample. The results are not included in the paper but are available upon request.

Table 7: Maximum likelihood estimates in binary logit models, treatment effects and determinants on offsetting behavior, all bookings, dependent variable: participation

Explanatory variables	(1)	(2)	(3)	(4)	(5)
r-25%	0.152*	0.177**	0.174**	0.169**	0.168**
	(0.0808)	(0.0819)	(0.0819)	(0.0820)	(0.0820)
r-50%	0.342***	0.368***	0.367***	0.363***	0.361***
	(0.0790)	(0.0799)	(0.0799)	(0.0799)	(0.0799)
r-75%	0.372***	0.399***	0.400***	0.394***	0.392***
	(0.0792)	(0.0803)	(0.0803)	(0.0803)	(0.0803)
1/3:1	-0.0338	-0.01000	-0.0120	-0.0121	-0.00464
	(0.0816)	(0.0825)	(0.0825)	(0.0825)	(0.0832)
1:1	0.227***	0.266***	0.263***	0.263***	0.285***
	(0.0807)	(0.0813)	(0.0813)	(0.0813)	(0.0887)
3:1	0.0779	0.106	0.102	0.102	0.170
	(0.0805)	(0.0813)	(0.0813)	(0.0813)	(0.130)
CO_2		-0.00899***			
		(0.00252)			
CO_2 per trip			-0.0141*	-0.0135*	
			(0.00785)	(0.00785)	
return ticket			-0.00264	-0.00203	-0.00725
			(0.0470)	(0.0470)	(0.0469)
group ticket			-0.297***	-0.296***	-0.298***
			(0.0768)	(0.0768)	(0.0768)
relative costs				-0.688***	-0.784***
				(0.200)	(0.269)
total CO_2 per trip					-0.00260
					(0.00399)
voucher		-0.379**	-0.378**	-0.391**	-0.391**
		(0.158)	(0.159)	(0.159)	(0.159)
info		1.899***	1.887***	1.888***	1.884***
		(0.183)	(0.182)	(0.182)	(0.182)
female		-0.105**	-0.109**	-0.109**	-0.109**
		(0.0428)	(0.0429)	(0.0429)	(0.0429)
recurrences	-0.131***	-0.114***	-0.114***	-0.113***	-0.112**
	(0.0440)	(0.0438)	(0.0437)	(0.0437)	(0.0437)
Constant	-0.982***	-0.863***	-0.823***	-0.820***	-0.911***
	(0.0580)	(0.0696)	(0.0924)	(0.0924)	(0.0726)
log likelihood	-6470.08	-6397.22	-6394.06	-6392.82	-6394.07
Observations	10,623	10,623	10,623	10,623	10,623

Note: Omitted treatment category is *control*, standard errors are clustered per ID, *** p<0.01, ** p<0.05, * p<0.1

Table 8: Maximum likelihood estimates in Tobit models, treatment effects and determinants of offsetting behavior, all bookings, dependent variable: payments

Explanatory variables	payment_tot (1)	payment _tot (2)	payment _tot (3)	payment_pass (4)	payment _pass (5)	payment _pass (6)
r-25%	4.377*	4.576**	4.469**	-0.158	-0.113	-0.162
	(2.342)	(2.265)	(2.275)	(1.230)	(1.175)	(1.180)
r-50%	9.491***	9.568***	9.492***	-0.410	-0.431	-0.463
	(2.271)	(2.190)	(2.197)	(1.142)	(1.092)	(1.096)
r-75%	10.79***	10.80***	10.62***	-2.765**	-2.834***	-2.920***
	(2.288)	(2.199)	(2.210)	(1.104)	(1.059)	(1.064)
1/3:1	2.228	2.818	2.856	-0.540	-0.287	-0.265
	(2.435)	(2.348)	(2.350)	(1.289)	(1.229)	(1.230)
1:1	16.80***	17.35***	17.40***	3.320**	3.514***	3.541***
	(2.598)	(2.470)	(2.503)	(1.297)	(1.224)	(1.240)
3:1	30.10***	30.60***	30.64***	1.020	1.210	1.227
	(3.021)	(2.911)	(2.915)	(1.267)	(1.210)	(1.210)
CO_2		0.817***			0.405***	
		(0.137)			(0.0650)	
CO_2 per trip			1.444***			0.690***
			(0.271)			(0.124)
return ticket			12.36***			6.040***
			(1.566)			(0.702)
group ticket			6.290**			3.253**
			(2.957)			(1.330)
relative price			-8.644***			-3.915***
			(1.374)			(0.595)
voucher		-9.417*	-10.06*		-3.662	-3.973*
		(5.202)	(5.252)		(2.300)	(2.335)
info		53.57***	53.92***		24.26***	24.47***
		(5.728)	(6.319)		(2.279)	(2.595)
female		-3.144**	-3.421**		-1.516**	-1.647***
		(1.346)	(1.352)		(0.603)	(0.607)
recurrences	-4.623***	-3.267**	-3.226**	-2.048***	-1.331**	-1.319**
	(1.392)	(1.326)	(1.322)	(0.636)	(0.599)	(0.599)
Constant	-40.87***	-49.36***	-55.56***	-13.30***	-17.38***	-20.24***
	(2.355)	(3.211)	(3.745)	(1.072)	(1.415)	(1.641)
log likelihood	-21102.9	-20971.0	-20968.4	-18625.8	-18479.2	-18478.8
Observations	10,623	10,623	10,623	10,623	10,623	10,623

Note: Omitted treatment category is *control*, robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

To shed further light on the dynamics of our contribution schemes we add treatment-specific time effects in our regression models. We study the interaction of treatment effects and recurrences both for participation and contribution levels by interacting *recurrences* with the respective treatment (Table 9). The estimation results on participation rates (columns 1-3) show negative trends for repeated bookings both in all price schemes, but being significant only for *r-50%* ($p < 0.01$) and *r-75%* ($p < 0.05$) (Table 9, columns 1-3). Similarly, we report a decreasing impact of *3:1* matching ($p < 0.1$). There is, however, statistical evidence that the provision of *1:1* matches increases the share of compensated bookings over time ($p < 0.1$). This suggests that bookers do not use alternating offsetting strategies in the presence of *1:1* matches. Rather the share of bookers increases over time.

With respect to compensation levels, we get a similar picture. There is a negative trend for all rebate schemes being significant for *r-50%* ($p < 0.01$) and *r-75%* ($p < 0.05$) (Table 9, columns 3-6). As before, there is a negative trend for 3:1 matching ($p < 0.1$) whereas the equal matching scheme (*1:1*) is the only incentive scheme where contributions do not decrease over time. We obtain the following result:

Result 7

For large rebates (r-50% and r-75%) we find a decreasing impact on participation over time. The effects of matching schemes seem to be more stable over time. In the long run, only the equal sharing rule (1:1) can maintain both higher participation and compensation levels for repeated bookings.

With respect to control variables, the previously significant drivers of compensation behavior, *group* and *female*, appear and exhibit similar signs and levels of significance as before.

Table 9: Maximum likelihood estimates in binary logit and Tobit models, treatment-specific time effects for repeated booking processes and determinants on offsetting behavior, dependent variable: participation or compensation

Explanatory variables	(1) participation	(2) participation	(3) participation	(4) compensation	(5) compensation	(6) Compensation
r-25%	0.183**	0.211**	0.203**	0.00270	0.00323	0.00302
	(0.0858)	(0.0871)	(0.0872)	(0.0131)	(0.0125)	(0.0125)
r-50%	0.416***	0.444***	0.439***	0.00510	0.00503	0.00508
	(0.0839)	(0.0850)	(0.0850)	(0.0121)	(0.0115)	(0.0116)
r-75%	0.422***	0.456***	0.449***	-0.0227*	-0.0231**	-0.0239**
	(0.0844)	(0.0857)	(0.0857)	(0.0117)	(0.0112)	(0.0113)
1/3:1	-0.0362	-0.0102	-0.0123	-0.00694	-0.00390	-0.00381
	(0.0871)	(0.0881)	(0.0881)	(0.0137)	(0.0131)	(0.0131)
1:1	0.183**	0.225***	0.222**	0.0267*	0.0300**	0.0305**
	(0.0863)	(0.0871)	(0.0871)	(0.0138)	(0.0131)	(0.0132)
3:1	0.113	0.144*	0.140	0.0152	0.0178	0.0178
	(0.0858)	(0.0867)	(0.0868)	(0.0135)	(0.0128)	(0.0128)
control X recurrences	-0.0179	0.0112	0.0130	-0.00888	2.88e-06	0.000648
	(0.115)	(0.114)	(0.114)	(0.0169)	(0.0162)	(0.0162)
r-25% X recurrences	-0.200	-0.181	-0.182	-0.0339*	-0.0252	-0.0261
	(0.125)	(0.124)	(0.124)	(0.0178)	(0.0169)	(0.0169)
r-50 X recurrences	-0.467***	-0.439***	-0.443***	-0.0654***	-0.0566***	-0.0578***
	(0.124)	(0.123)	(0.123)	(0.0165)	(0.0156)	(0.0154)
r-75% X recurrences	-0.301**	-0.304**	-0.297**	-0.0368**	-0.0292**	-0.0289**
	(0.121)	(0.123)	(0.123)	(0.0144)	(0.0137)	(0.0137)
1/3:1 X recurrences	-0.0171	0.000758	0.00129	-0.00244	0.00375	0.00504
	(0.109)	(0.108)	(0.108)	(0.0174)	(0.0162)	(0.0163)
1:1 X recurrences	0.197*	0.211*	0.213*	0.0221	0.0239*	0.0234*
	(0.112)	(0.113)	(0.112)	(0.0146)	(0.0142)	(0.0141)
3:1 X recurrences	-0.220*	-0.204*	-0.200	-0.0371**	-0.0318*	-0.0304*
	(0.123)	(0.122)	(0.122)	(0.0185)	(0.0178)	(0.0177)
CO_2		-0.00908***			0.00405***	
		(0.00253)			(0.000651)	
CO_2 per trip			-0.0144*			0.00679***
			(0.00785)			(0.00124)
return ticket			0.000964			0.0608***
			(0.0471)			(0.00702)
group ticket			-0.295***			0.0330**
			(0.0772)			(0.0133)
relative costs			-0.689***			-0.0387***
			(0.202)			(0.00591)
voucher		-0.374**	-0.387**		-0.0357	-0.0388*
		(0.159)	(0.160)		(0.0230)	(0.0234)
info		1.900***	1.888***		0.242***	0.244***
		(0.184)	(0.182)		(0.0229)	(0.0260)
female		-0.108**	-0.111***		-0.0154**	-0.0167***
		(0.0429)	(0.0430)		(0.00604)	(0.00607)
Constant	-1.002***	-0.883***	-0.835***	-0.135***	-0.176***	-0.204***
	(0.0613)	(0.0727)	(0.0944)	(0.0112)	(0.0146)	(0.0168)
log likelihood	-6458.33	-6385.39	-6381.03	-3884.49	-3738.09	-3737.55
Observations	10,623	10,623	10,623	10,623	10,623	10,623

Note: (1)-(3) logit regressions on participation, (4)-(6) Tobit regressions on contributions, omitted treatment category is control, robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Finally, we take a look at individual behavior after removing the incentive schemes (Table 10). In this stage (stage 3), no incentives are provided, all customers face the same decision situation. Observed bookings in the post intervention period allow us to study potential spill-over effects of the different stimuli during the time after their removal. In the long-run, *r-25*% leads to slightly lower participation in the offsetting program compared to the control group, while the remaining five treatments are followed by higher participation rates. Most of these differences, however, appear to be not statistically significant in our sample. Again, only the *1:1* matching scheme yields the highest, and the only statistically significant effect ($p < 0.10$). Hence, the *1:1* matching schemes induce spill-over effects and increase contributions even after their removal.

In a related study, Meier (2007) studies the long-run effects of two matching schemes (*1/4:1* and *1/2:1*). He observes decision behavior over a series of years and finds a short term positive effect in the year when the matching schemes were in act. In the subsequent year, when the matching schemes were removed, he finds negative effects. Over the full period of four years, including the treatment year, both effects cancel out such that no treatment effect remains. The treatment closest to Meier's setting is our *1/3:1* matching scheme where we also find smaller participation than in baseline, even though the difference is not significant. For stronger matching rates, however, we find positive effects in the long-run with the strongest results for the *1:1* matching rate. Hence, our findings suggest that Meier's results may not carry over to matching rates equal to one. This novel finding adds to the scarce evidence on the long-run effects of rebates and matching schemes and is summarized in our final result.

Result 8

There are positive spill-over effects from 1:1 matching schemes after their removal, increasing participation and contributions in subsequent bookings.

Table 10: Maximum likelihood estimates in binary logit and Tobit models, long-term effects after removal of intervention, dependent variable: participation or compensation

Explanatory variables	(1) participation	(2) participation	(3) participation	(4) compensation	(5) compensation	(6) compensation
r-25% (in stage 2)	-0.160	-0.161	-0.156	-0.0267	-0.0250	-0.0238
	(0.344)	(0.345)	(0.343)	(0.0491)	(0.0492)	(0.0490)
r-50% (in stage 2)	0.514	0.512	0.509	0.0841*	0.0833*	0.0832*
	(0.316)	(0.314)	(0.313)	(0.0457)	(0.0456)	(0.0454)
r-75% (in stage 2)	0.445	0.444	0.441	0.0615	0.0613	0.0624
	(0.311)	(0.312)	(0.312)	(0.0449)	(0.0449)	(0.0448)
1/3:1 (in stage 2)	0.142	0.141	0.131	0.0213	0.0211	0.0206
	(0.317)	(0.317)	(0.317)	(0.0455)	(0.0455)	(0.0454)
1:1 (in stage 2)	0.580*	0.581*	0.574*	0.0882*	0.0886*	0.0881*
	(0.323)	(0.323)	(0.322)	(0.0469)	(0.0469)	(0.0468)
3:1 (in stage 2)	0.356	0.357	0.349	0.0693	0.0697	0.0698
	(0.314)	(0.314)	(0.314)	(0.0456)	(0.0456)	(0.0455)
amountco2pertrack	-0.0438	-0.0438	-0.0369	0.00137	0.00140	0.00221
	(0.0390)	(0.0390)	(0.0396)	(0.00586)	(0.00585)	(0.00591)
retour	-0.584***	-0.583***	-0.587***	-0.0230	-0.0234	-0.0231
	(0.197)	(0.197)	(0.199)	(0.0295)	(0.0294)	(0.0295)
nr_pas2	-0.829	-0.826	-0.829	-0.0520	-0.0513	-0.0498
	(0.656)	(0.656)	(0.661)	(0.0958)	(0.0958)	(0.0961)
relative price	27.49	27.48	27.09	4.573	4.585	4.515
	(23.78)	(23.77)	(23.73)	(3.742)	(3.738)	(3.721)
voucher	-0.997	-0.993	-1.057	-0.138	-0.137	-0.141
	(0.724)	(0.724)	(0.742)	(0.103)	(0.104)	(0.105)
info	2.137***	2.140***	2.199***	0.233***	0.234***	0.243***
	(0.808)	(0.809)	(0.810)	(0.0648)	(0.0650)	(0.0654)
female	-0.165	-0.165	-0.151	-0.0233	-0.0237	-0.0224
	(0.168)	(0.168)	(0.168)	(0.0247)	(0.0247)	(0.0247)
recurrences		0.0179	0.00358		0.00543	0.00416
(in stage 3)		(0.171)	(0.177)		(0.0228)	(0.0232)
recurrences			0.137			0.0182
(in stage 2)			(0.110)			(0.0151)
Constant	-0.318	-0.342	-0.575	-0.223*	-0.230*	-0.263**
	(0.757)	(0.792)	(0.802)	(0.116)	(0.120)	(0.123)
log likelihood	-440.93	-440.92	-440.07	-286.32	-286.06	-285.35
Observations	827	827	827	828	827	827

Note: (1)-(3) logit regressions on participation, (4)-(6) Tobit regressions on contributions, omitted treatment category is *control (in stage 2)*, robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

5. Conclusion

Forming adequate institutions to enhance the private provision of public good is a complicated challenge. The joint decision on both the consumption of a private and the contribution to a public good may provide an opportunity to foster voluntary contributions. Carbon offsets serve as a prominent application of this concept since they provide the opportunity to displace pollution externalities in connection to an underlying harm-related consumption decision.

In this paper we examine voluntary contributions to a carbon offsetting program based on a large-scaled field experiment in the long-distance bus market in Germany. We systematically varied the individual payoff structure and introduced price rebates and matching grants in a randomized fashion.

Our results suggest price rebates to be more effective in stimulating participation while net contributions are higher in the matching schemes. We report a modest sensitivity to prices with diminishing marginal effects for large rebates and matches. An equal split of contributions between the traveler and the bus company, in form of *1:1* matches or a 50% price rebates, enhances the participation in the offsetting program in contrast to the baseline scenario while larger matches or rebates do not have an additional effect. Hence, the missing impact of increasing stimuli beyond the equal share does not seem to be limited to donation matches (Karlan and List 2007), but also holds for prices rebates in our context. One speculative explanation for this finding is that both larger matching rates and price rebates may provoke skepticism e.g., concerning the quality or the effectiveness of the carbon offset. Our most appealing finding is the dominance of the *1:1* matching scheme in the long-run. While the treatment effects of rebates fade away over time, only the *1:1* matching scheme enhances contributions when bookers are treated repeatedly. Even after removing the subsidies, we report higher participation rates and contribution levels for booker previously facing a *1:1* matching scheme. The outstanding position of the equal matching scheme is somewhat surprising. We speculate that the equal matching scheme may be the only intervention that attributes a normative character to the offsetting decisions in the sense of a social proof, leading bookers to stick to their previous choices.

The dominance of the *1:1* matching scheme may also contribute to the discussion on an acceptable burden sharing rule. The results indicate that a norm of 50-50 division possibly serves as an acceptable focal point on what could be a “fair” burden sharing concept between the producer and the consumer. Similar considerations hold for the 50% rebate scheme. This is in line with findings from the experimental literature showing that a large fraction of participants favor an equal split, even in dictator games where a single party determines the outcome (see Engel 2011 for a meta-study). There is, however, evidence that a higher degree of anonymity weakens the norm and leads to more selfish behavior which may lead to the hypothesis that people like to be *perceived* as fair (Andreoni and Bernheim 2009). Our results indicate that the linkage of public goods contributions to individual harm-related behavior might increase compliance with a 50-50 norm even if individual decisions are not observed by others.

These novel findings provide insights into the economics of environmental offsets and contribute to the discussion on how to successfully design interventions to foster individual efforts to mitigate greenhouse gas emissions. More generally, our analysis is one of the first randomized field trials to study public good contributions linked to a conventional consumption good. In our experiment, customers are given the possibility to offset their externalities just when they are about to purchase a conventional transportation good. Of course, this sequential decision structure differs from the classic impure public ("green") good setting where the consumer directly chooses between a conventional and a green good, e.g. between conventional and shade-grown coffee or between electricity from renewable or non-renewable resources. Nevertheless, the close connection between contributions and own responsibility remains the same. Our results suggest that the willingness to offset emissions beyond the harm level of related own behavior remains rather modest. It may thus be fruitful to extend this line of research to other contexts and choice structures. In particular, this may include decisions where individuals are able to independently determine their own contribution levels given the respective rebate or matching scheme, similar to the structure of charitable donation experiments.

Other possible directions for future research include the analysis of information settings on voluntary offsetting contributions. One specific aspect may address the role of feedback, social information or social proof. Recent field-experimental findings by Shang and Croson (2009) suggest social information on previous contributions to have comparable effects to matching grants or price rebates on donations to local charities.

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Appendix

Table A1: Mann-Whitney U (MW-U) tests on treatment differences (participation rate)

	Only first booking					
Treatment	*1:1*	*r-50%*	*3:1*	*r-75%*	*1/3:1*	*r-25%*
control	**-2.115**	**-4.790**	-1.252	**-5.015**	0.531	**-1.990**
	(0.0345)	(0.0000)	(0.2105)	(0.0000)	(0.5952)	(0.0466)
1:1		**-2.618**	0.881	**-2.850**	**2.633**	0.136
		(0.0088)	(0.3782)	(0.0044)	(0.0085)	(0.8915)
r-50%			**3.549**	-0.247	**5.304**	**2.774**
			(0.0004)	(0.8049)	(0.0000)	(0.0055)
3:1				**-3.780**	1.780	-0.749
				(0.0002)	(0.0750)	(0.4541)
r-75%					**5.526**	**3.007**
					(0.0000)	(0.0026)
1/3:1						**-2.512**
						(0.0120)

Note: According to a MW-U test, the null hypothesis states that the median of two independent observations is equal. The first booking per ID serves as an independent observation. We compare rows with columns and report both z – statistics and p – values (in parentheses).

Table A2: Mann-Whitney U (MW-U) tests on treatment differences (contribution levels)

	Only first booking					
Treatment	*1:1*	*r-50%*	*3:1*	*r-75%*	*1/3:1*	*r-25%*
control	**-2.018**	-1.344	-1.306	-0.004	0.502	-0.494
	(0.0436)	(0.1788)	(0.1916)	(0.9965)	(0.6159)	(0.6213)
1:1		1.113	0.709	**2.622**	**2.506**	1.727
		(0.2655)	(0.4783)	(0.0087)	(0.0122)	(0.0841)
r-50%			-0.222	**3.828**	1.926	0.453
			(0.8246)	(0.0001)	(0.054)	(0.6503)
3:1				1.591	1.779	0.929
				(0.1116)	(0.0753)	(0.3531)
r-75%					0.664	-1.885
					(0.5068)	(0.0594)
1/3:1						-1.020
						(0.3076)

Note: According to a MW-U test, the null hypothesis states that the median of two independent observations is equal. The first booking per ID serves as an independent observation. We compare rows with columns and report both z – statistics and p – values (in parentheses).

Table A3: Average marginal and discrete probability effects of explanatory variables on participation decision

Explanatory variables	dy/dx	[95% Conf. Intervall]	
r-25%	0.040**	0.004	0.076
r-50%	0.089***	0.054	0.124
r-75%	0.095***	0.060	0.130
1/3:1	-0.004	-0.041	0.032
1:1	0.046**	0.010	0.082
3:1	0.027	-0.009	0.063
CO2 per trip	-0.003**	-0.007	0.000
return ticket	0.003	-0.017	0.024
group ticket	-0.054***	-0.088	-0.021
relative cost	-0.148	-0.236	-0.059
voucher	-0.054	-0.126	0.017
info	0.391***	0.318	0.464
female	-0.019**	-0.038	0.000

Note: Average marginal and discrete probability effects are calculated after the ML estimation reported in Table 3, column (6), *** $p<0.01$, ** $p<0.05$,

Table A4: Average marginal and discrete probability effects of explanatory variables on compensation levels

Explanatory variables	dy/dx	[95% Conf. Intervall]	
r-25%	0.237	-2.245	2.719
r-50%	0.376	-1.921	2.673
r-75%	-2.309**	-4.541	-0.077
1/3:1	-0.420	-3.020	2.181
1:1	3.164**	0.519	5.809
3:1	1.675	-0.873	4.224
CO2 per trip	0.677***	0.414	0.939
return ticket	6.271***	4.808	7.734
group ticket	3.795***	1.019	6.570
relative cost	-3.702***	-4.817	-2.586
voucher	-1.932	-7.016	3.152
info	24.354***	19.152	29.556
female	-1.314**	-2.245	-0.350

Note: Average marginal and discrete probability effects are calculated after the ML estimation reported in Table 5, column (6), *** $p<0.01$, ** $p<0.05$

Table A5: Alternative capture of treatment effects

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
unit price -25%	0.191**	0.184**	0.172**	0.191**	0.0863	0.106
	(0.0794)	(0.0823)	(0.0869)	(0.0882)	(0.0760)	(0.0772)
unit price -50%	0.420***	0.435***	0.404***	0.424***	0.359***	0.385***
	(0.0785)	(0.0798)	(0.0849)	(0.0860)	(0.0761)	(0.0773)
unit price -75%	0.393***	0.448***	0.427***	0.452***	0.451***	0.471***
	(0.0788)	(0.0826)	(0.0852)	(0.0865)	(0.0839)	(0.0859)
match	-0.255***	-0.182***				
	(0.0493)	(0.0647)				
unit price -25% X match			-0.217**	-0.198**		
			(0.0875)	(0.0892)		
unit price -50% X match			-0.219***	-0.161*		
			(0.0845)	(0.0927)		
unit price -75% X match			-0.325***	-0.196		
			(0.0842)	(0.138)		
share matched CO_2					-0.125***	-0.0801*
					(0.0266)	(0.0452)
total CO_2 per trip		-0.00507		-0.00488		-0.00477
		(0.00330)		(0.00428)		(0.00429)
group Ticket		-0.263***		-0.263***		-0.262***
		(0.0820)		(0.0821)		(0.0821)
return Ticket		0.0102		0.00983		0.0106
		(0.0503)		(0.0503)		(0.0503)
relative cost		-0.793***		-0.801***		-1.050
		(0.292)		(0.303)		(1.086)
voucher		-0.263		-0.263		-0.264
		(0.176)		(0.176)		(0.176)
info		1.875***		1.876***		1.877***
		(0.184)		(0.184)		(0.183)
female		-0.0905*		-0.0905*		-0.0918**
		(0.0463)		(0.0463)		(0.0463)
Constant	-0.993***	-0.924***	-0.993***	-0.926***	-0.993***	-0.923***
	(0.0620)	(0.0745)	(0.0620)	(0.0778)	(0.0620)	(0.0786)
log likelihood	-5542.29	-5472.50	-5541.77	-5472.44	-5544.57	-5474.91
Observations	9,024	9,024	9,024	9,024	9,024	9,024

Note: Omitted treatment category is *control*, robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A6: Gender specific regressions on participation decision and contribution levels

Explanatory variables	(1) participation	(2) participation (males only)	(3) participation (females only)	(4) compensation	(5) compensation (males only)	(6) compensation (females only)
p-25%	0.314***	0.260**	0.148	1.409	0.987	0.0642
	(0.114)	(0.129)	(0.125)	(1.675)	(1.911)	(1.740)
p-50%	0.549***	0.555***	0.353***	1.551	1.898	0.208
	(0.113)	(0.126)	(0.130)	(1.603)	(1.762)	(1.772)
p-75%	0.577***	0.626***	0.364**	-1.133	-0.579	-2.122
	(0.113)	(0.126)	(0.145)	(1.580)	(1.711)	(1.972)
1/3:1	0.102	0.0757	-0.115	0.760	0.269	-1.046
	(0.115)	(0.132)	(0.122)	(1.720)	(1.999)	(1.767)
1:1	0.343***	0.375***	0.0811	4.336**	5.146**	1.431
	(0.114)	(0.128)	(0.121)	(1.749)	(2.082)	(1.763)
3:1	0.251**	0.224*	0.0395	2.843*	2.413	1.071
	(0.114)	(0.127)	(0.122)	(1.693)	(1.918)	(1.764)
CO_2 per trip	-0.0167**	-0.0130	-0.0251*	0.676***	0.812***	0.416**
	(0.00845)	(0.0121)	(0.0130)	(0.134)	(0.212)	(0.181)
return ticket	0.0140	-0.0153	0.0339	6.260***	6.254***	6.083***
	(0.0504)	(0.0743)	(0.0688)	(0.747)	(1.125)	(0.988)
group ticket	-0.263***	-0.0978	-0.451***	3.786***	6.497***	0.772
	(0.0821)	(0.111)	(0.124)	(1.417)	(2.000)	(2.017)
relative price	-0.711***	-0.835***	6.150	-3.683***	-3.759***	172.8
	(0.219)	(0.288)	(8.203)	(0.568)	(0.680)	(124.4)
voucher	-0.265	-0.126	-0.468*	-1.963	0.345	-5.916
	(0.176)	(0.238)	(0.275)	(2.597)	(3.692)	(3.872)
info	1.884***	1.871***	1.904***	24.39***	26.38***	22.87***
	(0.184)	(0.280)	(0.242)	(2.655)	(5.042)	(2.418)
female	-0.121**			-1.631**		
	(0.0497)			(0.695)		
female * control	0.234*			2.237		
	(0.136)			(1.997)		
Constant	-0.932***	-0.971***	-0.823***	-21.59***	-23.62***	-20.07***
	(0.116)	(0.137)	(0.148)	(2.036)	(2.977)	(2.306)
log likelihood	-5469.69	-2571.67	-2893.98	-15974.25	-7626.33	-8339.56
Observations	9,024	4,197	4,827	9,024	4,197	4,827

Note: Omitted treatment category is *control*, robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A7: Average marginal effects of explanatory variables on participation decision, all bookings

Explanatory variables	dy/dx	[95% Conf. Intervall]	
r-25%	0.035**	0.002	0.068
r-50%	0.075***	0.043	0.107
r-75%	0.081***	0.049	0.113
1/3:1	-0.003	-0.036	0.031
1:1	0.054***	0.021	0.087
3:1	0.021	-0.012	0.054
CO_2 per trip	-0.003*	-0.006	0.000
return Ticket	-0.000	-0.019	0.019
group Ticket	-0.061***	-0.092	-0.030
relative price	-0.142***	-0.222	-0.061
voucher	-0.081**	-0.449	-0.163
info	0.389***	0.317	-0.461
female	-0.022**	-0.040	-0.005
recurrences	-0.023***	0.041	0.006

Note: Average marginal and discrete probability effects are calculated after the ML estimation reported in Table 7, column (4), *** p<0.01, ** p<0.05, * p<0.1

Table A8: Average marginal effects of explanatory variables on compensation levels, all bookings

Explanatory variables	dy/dx	[95% Conf. Intervall]	
r-25%	-0.162	-2.475	2.150
r-50%	-0.463	-2.610	1.684
r-75%	-2.920***	-5.005	-0.835
1/3:1	-0.265	-2.676	2.146
1:1	3.541***	1.112	5.971
3:1	1.227	-1.145	3.599
CO_2 per trip	0.690***	0.447	0.933
return Ticket	6.040***	4.665	7.415
group Ticket	3.253**	0.647	5.859
relative price	-3.915***	-5.082	-2.748
voucher	-3.973*	-8.549	0.603
info	24.467***	19.382	29.552
female	-1.647***	-2.836	-0.458
recurrences	-1.319***	-2.492	-0.145

Note: Average marginal and discrete probability effects are calculated after the ML estimation reported in Table 8, column (6), *** p<0.01, ** p<0.05, * p<0.1

Figure A1: Overview on field experimental setting

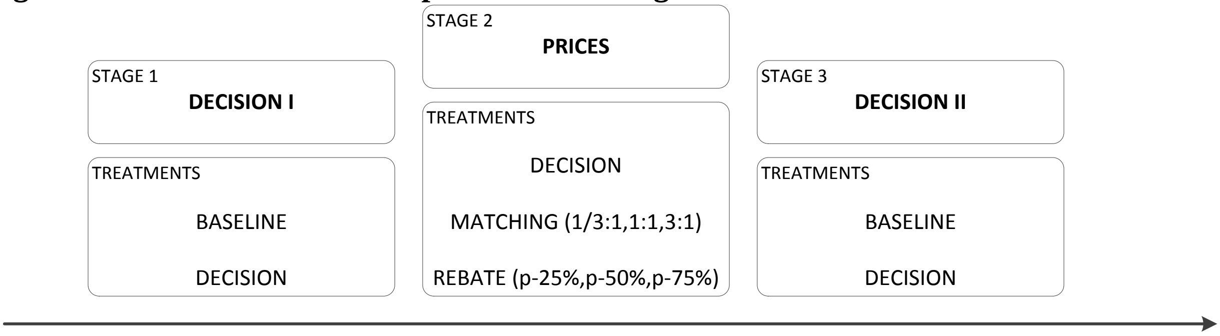
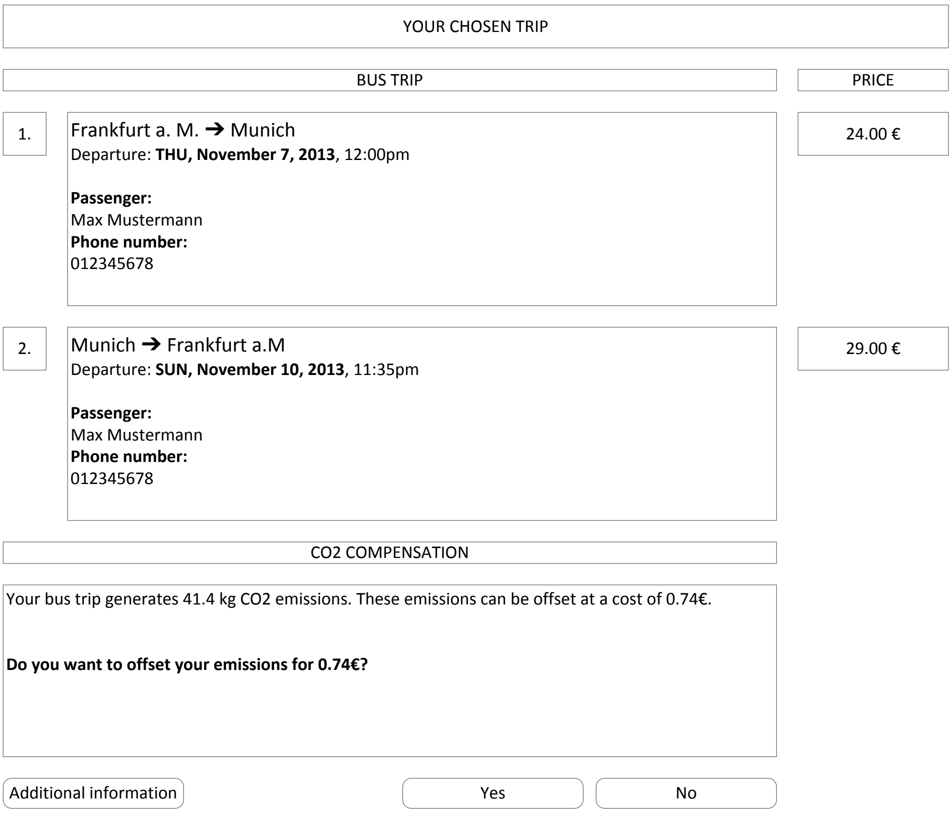


Figure A2: Experimental design

Translated screenshot: control



Translated screenshot: *r-25%*

YOUR CHOSEN TRIP

BUS TRIP		PRICE
1.	Frankfurt a. M. ➔ Munich Departure: **THU, November 7, 2013**, 12:00pm **Passenger:** Max Mustermann **Phone number:** 012345678	24.00 €
2.	Munich ➔ Frankfurt a.M Departure: **SUN, November 10, 2013**, 11:35pm **Passenger:** Max Mustermann **Phone number:** 012345678	29.00 €

CO2 COMPENSATION

Your bus trip generates 41.4 kg CO2 emissions. These emissions can be offset at a cost of 0.74€.

Due to a campaign, we support your contribution to climate protection during this trip and we will cover a fourth of the related offsetting cost. For each € of your contribution we will immediately reimburse 0.25€. As a result, you will pay 0.56 € instead of 0.74 €.

Do you want to take part in the campaign and offset your emissions for 0.56€?

Additional information | Yes | No

Translated screenshot: *1/3:1*

YOUR CHOSEN TRIP

BUS TRIP		PRICE
1.	Frankfurt a. M. ➔ Munich Departure: **THU, November 7, 2013**, 12:00pm **Passenger:** Max Mustermann **Phone number:** 012345678	24.00 €
2.	Munich ➔ Frankfurt a.M Departure: **SUN, November 10, 2013**, 11:35pm **Passenger:** Max Mustermann **Phone number:** 012345678	29.00 €

CO2 COMPENSATION

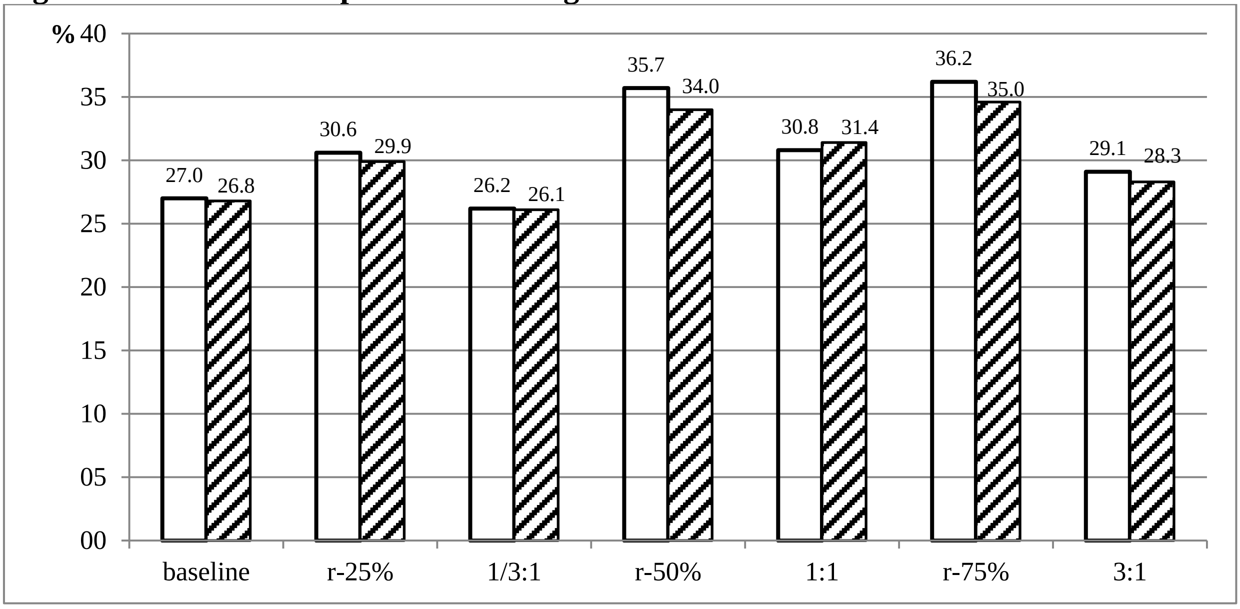
Your bus trip generates 41.4 kg CO2 emissions. These emissions can be offset at a cost of 0.74€.

Due to a campaign, we support your contribution to climate protection during this trip and we will increase, at our expenses, the amount you offset by 1/3. For each kilogram you compensate we will additionally compensate 1/3 kg CO2. As a result, 55.2 kg instead of 41.4 kg CO2 will be offset.

Do you want to take part in the campaign and offset your emissions for 0.74€?

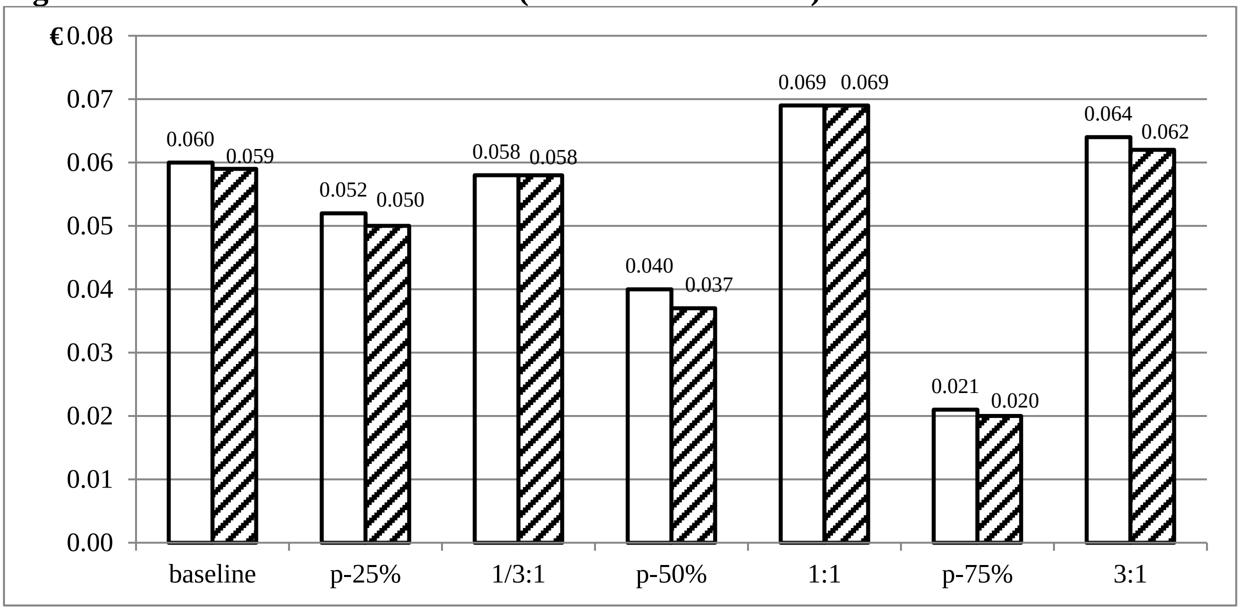
Additional information | Yes | No

Figure A3: Share of compensated bookings in %



Note: The first bar represents the share of compensated bookings for the first booking decision only. The second striped bar depicts the data for all booking decisions.

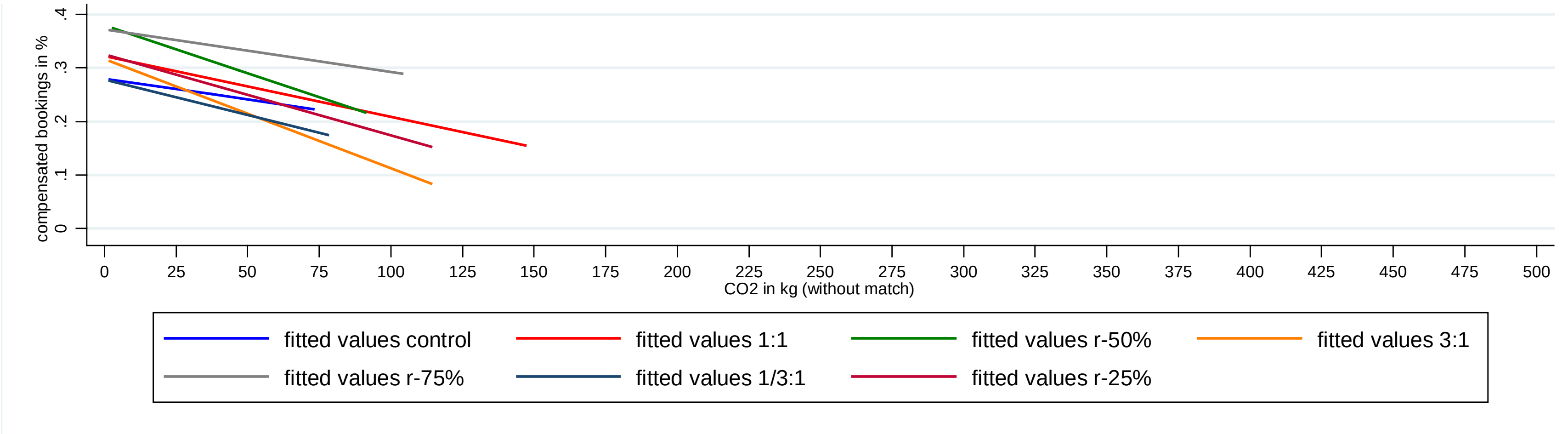
Figure A4: Customers' contributions (net of incentive costs)



Note: The first bar represents customers' net contributions bookings for the first booking decision only. The second striped bar depicts the data for all booking decisions.

Figure A5: Share of compensated bookings for different amounts of CO_2

excluding matches amounts:



including matched amounts: