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Title: Large but diminishing effects of climate action nudges under rising costs

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Abstract

Behavioural public policy has received broad research attention, particularly in the domain of motivating pro-environmental behaviours. We investigate how far the efficacy of arguably one the most popular behavioural policy tools (i.e., green 'default change' nudges) depends on the associated cost. Based on a field study involving carbon offsets for over 30,000 flights booked by more than 11,000 airline customers, we show that green defaults have a large effect on voluntary climate action, even when several hundreds of euros are at stake. The effect fully vanishes only as costs approach approximately 800 Euros.

Main text

Behavioural science has developed powerful tools to promote behavioural change through subtle alterations in the decision architecture consumers encounter, sometimes in collaboration with companies[1–4]. Many changes to decision architectures are motivated based on "paternalistic" reasoning, meaning that they intend to improve the welfare of the decision-maker, for example decreasing old-age poverty[5] or increasing health outcomes[6]. Other changes attempt to address externalities, promoting the creation of public goods (e.g., deceased organ availability[7], charitable giving[8]). In the domain of climate change mitigation, such interventions can strongly increase the number of consumers who sign up for a green energy contract[9,10], reduce their residential energy use[11,12], switch to a more cost-effective energy contract[13], or increase their willingness to buy environmentally-friendly consumer goods[14]. In previous studies, behavioural "nudges" either led to financial improvements for households (e.g., resulting in a reduction of one's energy bill) or had no or only trivially negative impact on one's financial wellbeing. Yet, whereas climate action is typically beneficial for society as a whole, it can come at a non-negligible price tag to the individual decision-maker. In order to gauge the effectiveness of behavioural interventions for climate change mitigation, it is therefore important to understand whether and how the response to behavioural interventions changes as the individual cost that is associated with the desired response increases.

The effectiveness of nudges in such "high cost" scenarios is, however, largely unknown. As was recently pointed out by Sunstein[15] in the context of climate nudges, "[…] a great deal remains to be learned. It makes sense to think that when and where the cost of green energy is high, the opt-out rate will be higher, but how much higher?" (p. 1). And in fact, despite recent laboratory evidence on the stability of people's inclination to rely on decision short-cuts (i.e., heuristics) even in high-cost scenarios[16], a systematic analysis of the efficacy of green 'default change' nudges under varying cost in the field is still missing. Here, we present results from a field study that exploits defaults in a choice setting with strongly varying financial consequences attached to voluntary climate action.

Our data come from a platform for the compensation of flight-related CO_2 emissions operated by a large European airline. Specifically, we rely on voluntary payments for offsetting by 11,159 airline customers of 30,522 trips between December 2019 and February 2020. Offsetting cost varied from negligible amounts (0.51 EUR) to extremely high stakes (2,877.17 EUR), allowing a systematic analysis of the default efficacy under varying financial consequences. The total compensation revenue raised in the context of our study was 559,126.30 EUR.

Customers who consider compensating their flight are directed to the platform. Flights can only be fully compensated, but customers decide on *how fast* they would like to offset, with faster offsets being more expensive. The fast option compensates through purchasing "Sustainable Aviation Fuel" (SAF). SAF is an alternative jet fuel that leads to 80% lower emissions compared to standard kerosene. Compensations in form of SAF cause a change in the total fuel mix of the airline operating the platform, therefore resulting in a consequential greenhouse gas emission reduction in the aviation industry. The slow option compensates through tree planting, which results in offsetting the emissions over a period of twenty years.

Compensation through tree planting is substantially cheaper than through SAF. As an example, a flight from Zurich (CH) to Los Angeles (USA) results in carbon emissions of 641.21 kg CO_2-eq. for one passenger flying in the economy class. Immediate offsetting through SAF is priced at 416.79 EUR, whereas slow offsetting by planting trees is priced at only 12.82 EUR. Customers can freely choose a mix between these two extremes, zero and 20 years to offset, on the entire continuum in increments of 0.2 years, by moving a slider to the preferred position. This way, they choose different speeds of compensation at different price tags. Figure 1 shows the decision screen of the customer.

The decision architecture involves the selection of a pre-defined slider position – the default. For each customer arriving at the online platform, the slider moves once between the two extremes while dynamically updating the price information, and stops at one of six pre-defined defaults (8, 10, 12, 14, 16, or 18 years). This signals to the customer that the slider can be shifted. After the slider stops, the customer can move it to the desired position, observe how much the offset costs and then proceed to the payment page.

Results

Our central result is that defaults are surprisingly effective in steering behaviour even when they are associated with substantial individual costs. Figure 2 illustrates the high efficacy for each of the six defaults. Overall, 43.38 % of the travellers stick exactly to the default value they were exposed to (see Supplementary Figure 1 for the entire distribution of all behavioural responses). Importantly, even if customers do not exactly choose the respective default, deviations from it are strongly compressed around the default. As a result, 49.32% of the decisions are made within +/- one year (i.e., 5% of the total range of available decisions) of the default-setting, including the exact default value. A total of 59.57% of decisions are made within +/- two years (i.e., 10% of the decision range) of the default. The default has a statistically significant effect on the decision with respect to where the final decision is logged, even for people explicitly moving away from the default (simple model: $B = 0.44$, 95% *CI*: 0.34 – 0.53, $p < 0.001$, two-tailed; Supplementary Table 1, further regression models in Supplementary Tables 2-6 provide more detailed results including controls).

The efficacy of defaults, however, varies with the associated cost. Defaults that come at a cheaper price tag more forcefully affect passenger' decision-making compared to defaults that are more expensive. To capture the impact of this price variation, we normalize the price tag of a default by comparing it to the cheapest possible offset for a given flight. This variable shows the price premium associated with choosing the default as compared to the cheapest compensation option. Based on a Logit regression, Figure 3 displays the estimated probability of sticking to the default as a function of this variable. Supplementary Tables 7 and 8 provide additional analyses supporting this result. As Figure 3 suggests, about 50% of the customers tend to stick to the default when the difference to the cheapest alternative is very small (i.e., <50 Euros), but this number decreases at cost go up. While there is still a substantial number of travellers willing to pay hundreds of euros for the default compensation scheme, Figure 3 shows that costs become prohibitive for everybody as they approach approximately 800 Euros. Descriptively, 776.18 Euros is the most expensive default that was kept by a passenger. Supplementary Table 11 shows the full descriptive results of passengers sticking to defaults at various cost levels.

Further evidence about the cost sensitivity comes from customers who deviate from the default. 64.89% of those customers chose a cheaper compensation scheme (i.e., they put more weight on tree planting). This pattern occurred with all defaults – including those that are relatively cheap (as shown in Figure 4) – and it is statistically highly significant (all χ^2-tests of proportions against proportion of available cheaper choices are significant at the level of $p < 0.001$; see also regressions in Supplementary Tables 9 and 10, depicted in Supplementary Figure 2).

Discussion

Taken together, our study shows both the strengths and limits of defaults. Defaults affect climate action even when it comes at substantial economic costs, yet decision-makers respond price-sensitively to those defaults in ways that eventually render the defaults ineffective.

Three cautionary remarks are in order here. First, we emphasize that our data only include customers who wanted to offset their emissions in the first place and who were not subsequently deterred from defaults and offsetting costs, which limits our observations and conclusions about the overall effects of the default setting on behaviour (see Supplementary Figure 4). Second, while the online platform conveys the impression that both means of offsetting (planting trees and SAF) are equally effective, tree planting has been frequently criticized[16–19]. Compared to SAF offsetting, tree planting is not only slower and cheaper, its effectiveness is also more uncertain. SAF may therefore be perceived as a superior offsetting technology. However, our results suggest that this does not systematically affect default efficacy, as all defaults have proven highly effective (see Fig. 2). Third, as the platform set a-priori quotas for respective default values, our field study did not fully randomize individuals into distinctive default values. Thus, this field study should not be seen as conclusive evidence on the causal impact of climate nudges on behaviour.

Our results have several implications. Most behavioural design studies involve financially beneficial or trivially negative stakes (i.e., saving energy, increasing pensions, etc.; for a review, see Kaiser et al., 2020[17]), and are typically meant as substitutes or supplements to more standard economic interventions. We show that the defaults' effectiveness to change behaviour is not limited to such specific circumstances. Indeed, the fact that defaults may play a diminished, albeit crucial role when the financial costs borne by the decision-makers are high suggests an important role for behavioural interventions that complement standard economic incentives for climate action such as carbon pricing.

While our naturally occurring field data does not allow identifying the exact underlying psychological mechanisms, one plausible explanation for the diminishing effectiveness of defaults is that higher cost may involve different cognitive processes. More costly defaults may activate people's "System 2" thinking, which tends to be slower and more analytical, whereas cheaper defaults may more likely be processed in "System 1", which tends to be fast and automatic[18]. Other explanations include the fact that, if decision-makers are budget-constrained, high-cost defaults are more likely to exceed such budgets than low-cost defaults. Indeed, we believe that our finding is so strong – and likely robust – because such different, complementary mechanisms all point in the same direction.

We finally emphasize that our study, even when proving the surprising effectiveness of defaults, does not necessarily imply that climate action nudges are an acceptable tool to protect the climate. While climate action may benefit society, it is often not in one's individual self-interest, especially when the individual costs can become very high as in our context. Moreover, poorer households may be particularly prone to stick to defaults and could thus be disproportionately affected by expensive nudges[12, 22]. Such ethical[20–22], welfare-related, and distributional issues[22, 26] need to be better understood and more systematically considered before people are nudged into costly climate action. Because climate action nudges can be effective even when cost is substantial, this is particularly so when the behavioural change is induced by the decision architecture designed by profit-maximizing companies.

Methods

The carbon-offsetting platform of a large European airline holding company allowed us to access their complete transaction data from the three months between December 1, 2019 and February 29, 2020. During this time, a total of 11,159 customers bought carbon offsetting for 30,522 trips (i.e., individual flight-passenger combinations) spending a total of 559,126.30 EUR.

Access to the platform is directly embedded in the booking process of two of the company's airlines as well as the internal staff booking tool of the company. Additionally, the offsetting platform is open to any customer wishing to offset her carbon emissions from a particular flight. Of the transactions in our dataset, 65.58% come from one of the airlines, 28.59% from the other, 4.24% from other flights, and 1.59% from the staff's booking tool.

After specifying their flight details either through the airlines' booking tools or directly on the offsetting platform (origin, destination, flight date, booking class and number of passengers are the minimum required information for each flight), customers are directed to the decision screen (see Fig. 1). The decision screen consists of a movable slider showing the years to offset on a continuum between a pictogram of drop on the left side (representing immediate offsetting through buying sustainable aviation fuel, SAF) and a tree on the right side (representing long-term offsetting through tree planting) beneath the heading "How fast do you want to offset your carbon emission?". When first landing on the decision screen, the slider moves from the left-most to the right-most position, and then back to the pre-determined default position (either 8, 10, 12, 14, 16 or 18 years). This way, customers are made aware that they can freely move the slider to their preferred position. The pre-determined slider position served as the respective default for a respective customer. On the right side of the screen, a summary of the flight details is shown (including the total carbon emission) and the total cost of the current slider position given this customer's total carbon emission. The cost for one kg CO2-eq ranges from 0.02 EUR for the cheapest option (i.e., only planting trees) to 0.50 EUR for the most expensive option (i.e., only buying SAF). With a median emission of 229.13 kg CO2-eq, this means the median-emission customer faced an overall choice range between 4.58 EUR and 114.56 EUR and a default position ranging between 15.31 EUR and 69.15 EUR.

As our study resulted in different cell sizes for the respective defaults (8 years: n = 113; 10 years: n = 3117; 12 years: n = 345; 14 years: n = 1199: 16 years: n = 3465: 18 years: n = 2920), we performed several ANOVAs to test for potential differences between default values among our relevant covariates (see Supplementary Tables 12 to 15 and Supplementary Figures 5 to 9). As there were differences among mean CO_2 emission levels and mean cost of keeping the default between the pre-selected default values, we implemented a propensity score matching to align the CO_2 levels and cost of keeping the default. We present the means and standard deviations for the relevant covariates conditional on the default values based on the new (matched) subsamples (see Supplementary Tables 12 to 15 and Supplementary Figures 5 to 9) and replicate Figure 2 from the main manuscript (Supplementary Figures 8 and 10). Our results indicate that there was no systematic bias driving the default effect.

Data availability

Anonymized raw data is available on the Open Science Framework (https://osf.io/rd7sy) in accordance with a data protection agreement with the airline partner (e.g., passenger IDs replaced with other unique IDs, etc.).

Code Availability

Results reported in the main text and supplementary material can be reproduced using the statistical code published via the Open Science Framework (https://osf.io/rd7sy). All data has been analysed using the open-source software R.

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Author Contribution Statement

SB, OL, AK, FS, AO, and AW conceptualized the study. SB, FS, AO, and AW determined the methodology. SB, FS, and AW analysed the data. OL and AK curated the data. SB, FS, and AW wrote the initial draft. SB, OL, AK, FS, AO, and AW commented on and revised the drafts. SB, FS, and AW visualized the results. SB and AO supervised OL, AK, and FS. SB administrated the project. SB and AO acquired funding.

Competing Interests Statement

All authors declare that they have no competing interests.

Figure Legends/Captions

Fig. 1| Decision screen for customers willing to offset their flight on the company's platform. This figure presents a stylized version of a decision screen for the default of 8 years and for a flight from Zurich to Los Angeles on July 12, 2019 for a European customer (paying in EUR).

Fig. 2| Behavioural "stickiness" to the pre-selected default settings for each of six default values employed in the field study. Here, we show the behavioural efficacy of the pre-selected default for each of the six default settings. Bars represent the proportion of decision-makers choosing the particular compensation scheme originating from the respective default (blue bars) versus not (yellow bars). All differences are statistically significant at the level $P < 0.001$ (8 years: $\chi^2(1)= 2211.6$, 95% CI: 0.30-1; 10 years: $\chi^2(1)= 2428.8$, 95% CI: 0.35-1; 12 years: $\chi^2(1)= 2416.8$, 95% CI: 0.30-1; 14 years: $\chi^2(1)= 2973.5$, 95% CI: 0.34-1; 16 years: $\chi^2(1)= 2994.6$, 95% CI: 0.37-1; 18 years: $\chi^2(1)= 3904.2$, 95% CI: 0.48-1). Note that the comparison group for each default consists of the entirety of customers exposed to the other five defaults (i.e., the web-design requires that the slider is positioned somewhere). The number of observations subjected to various defaults differed, taking values of $n_{8\ \text{years}} = 113$; $n_{10\ \text{years}} = 3117$; $n_{12\ \text{years}} = 345$; $n_{14\ \text{years}} = 1199$; $n_{16\ \text{years}} = 3465$; $n_{18\ \text{years}} = 2920$.

Fig. 3| Probability of sticking to default (blue line) or within two-year range (yellow line) depending on the associated cost, relative to cheapest offsetting option. Estimates were obtained from logit regression with default-sticking (blue line) or default-sticking within two years (yellow line) as the dependent variable and the cost of keeping the default as the independent variable. The independent variable was calculated by using the cost attached to the default minus the cheapest possible offsetting option. The corresponding regression results are displayed in Supplementary Table 5. The centre lines refers to the estimate, the shaded areas refers to the 95% confidence interval.

Fig. 4| Proportion of customers moving towards a cheaper offsetting scheme among all customers deviating from the default compared to the available share of cheaper options. The results show that, for any given default, the slider is moved more often to the cheaper direction than a uniform distribution of genuine willingness-to-pay would suggest. For example, in a default set to 16 years, only 19.80% of the available choices are at less expensive levels, but 63.99% of observed decisions are made in this range. The same logic applies to all other defaults. Among these choices of cheaper-than-default options, most people even opt for the cheapest available choice (i.e., 20 years to offset, see also Supplementary Figure 3). The point refers to the proportion of decisions made at a cheaper default. The surrounding error bars indicate 95% confidence intervals.

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How fast do you want to offset your carbon emission?

8 years

Sustainable Aviation Fuel
SAF (synthetic kerosene) reduces carbon emissions immediately (0 years)

Trees compensate carbon emissions in the long run (20 years).

Your flight details

PAX	Origin	→	Destination	CO2
1	**ZRH**	**→**	**LAX**	**641.21 kg**
Total				**641.21 kg**

Voucher Code (optional)

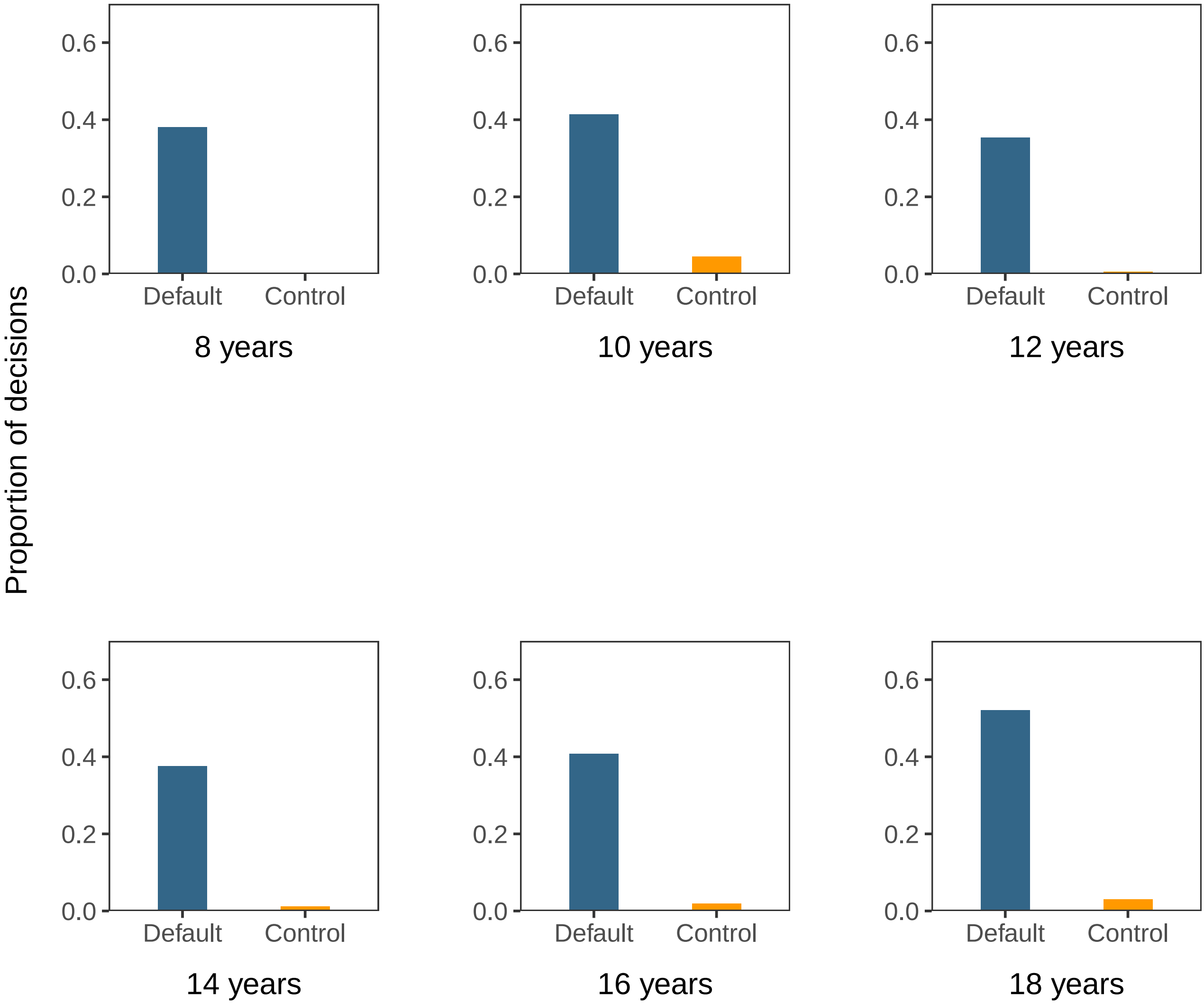
Do you have a voucher code?

The price for your offset EUR▼

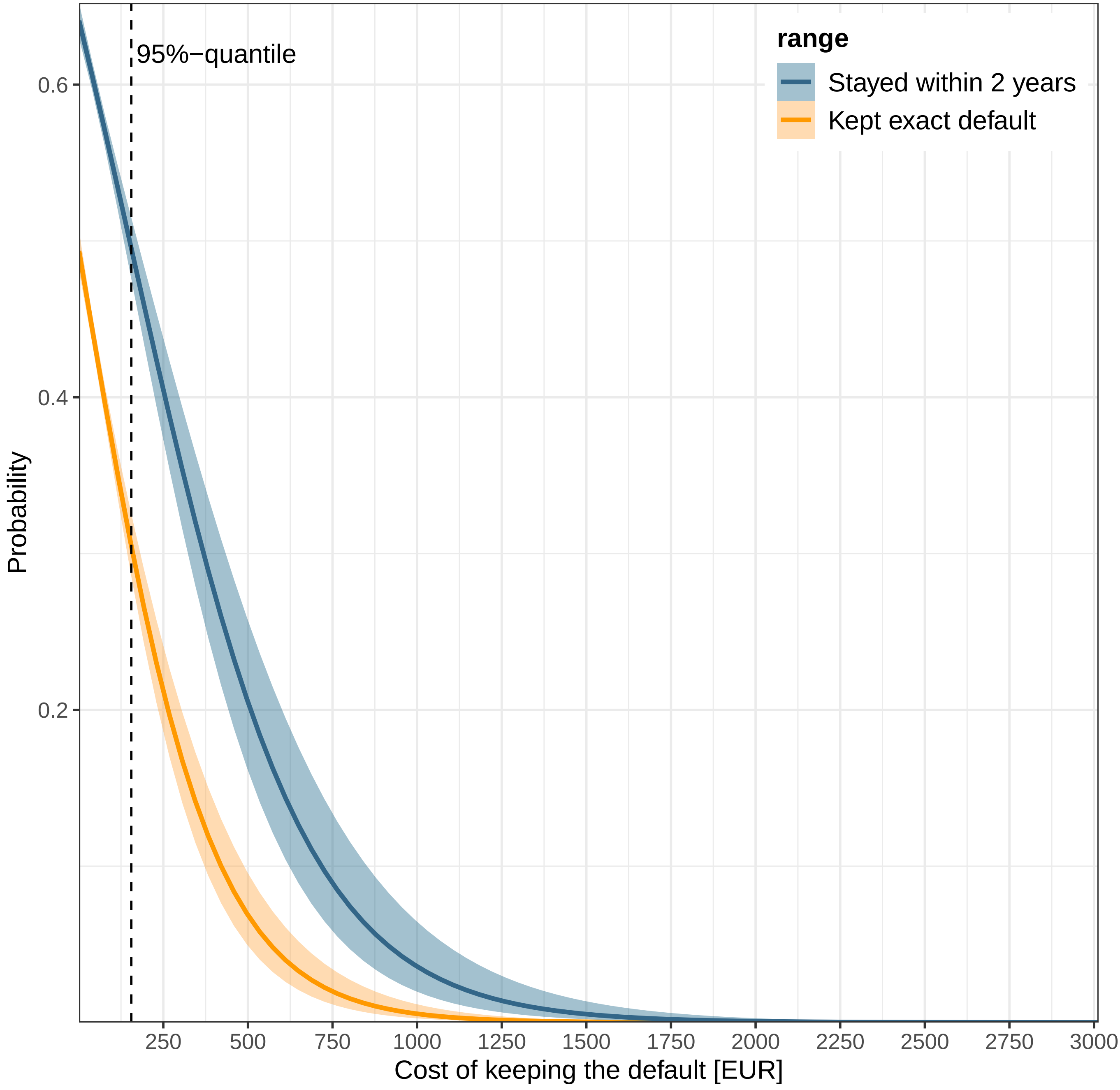
€ 255.10

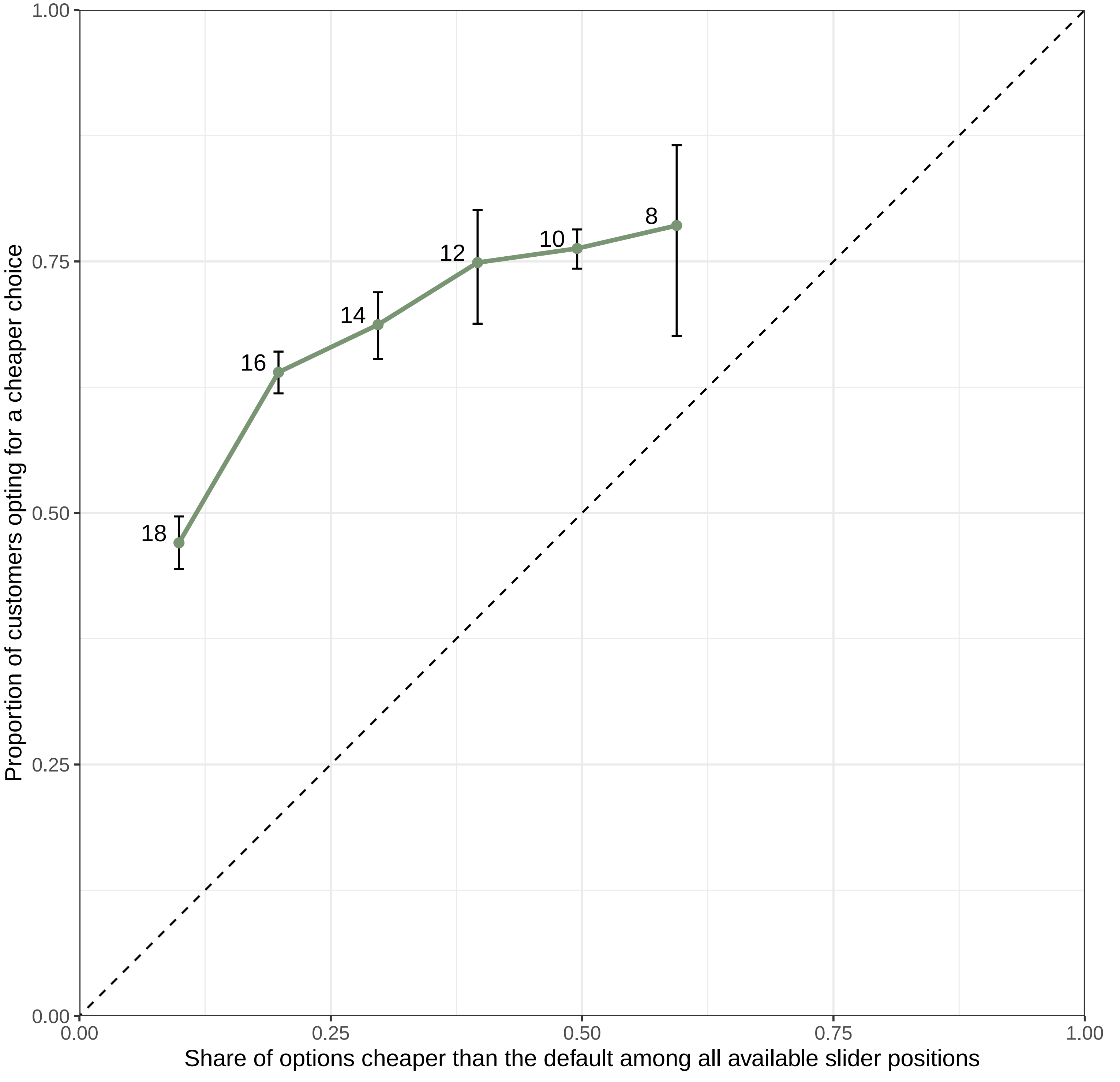
Continue with my account

Continue as guest



Proportion of decisions
0.6
0.4
0.2
0.0
Default
Control
8 years
10 years
12 years
14 years
16 years
18 years


95%−quantile
range
Stayed within 2 years
Kept exact default
Probability
0.6
0.4
0.2
250
500
750
1000
1250
1500
1750
2000
2250
2500
2750
3000
Cost of keeping the default [EUR]



1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
Proportion of customers opting for a cheaper choice
Share of options cheaper than the default among all available slider positions
18
16
14
12
10
8

Supplementary Information for

Large but diminishing effects of climate action nudges under rising costs

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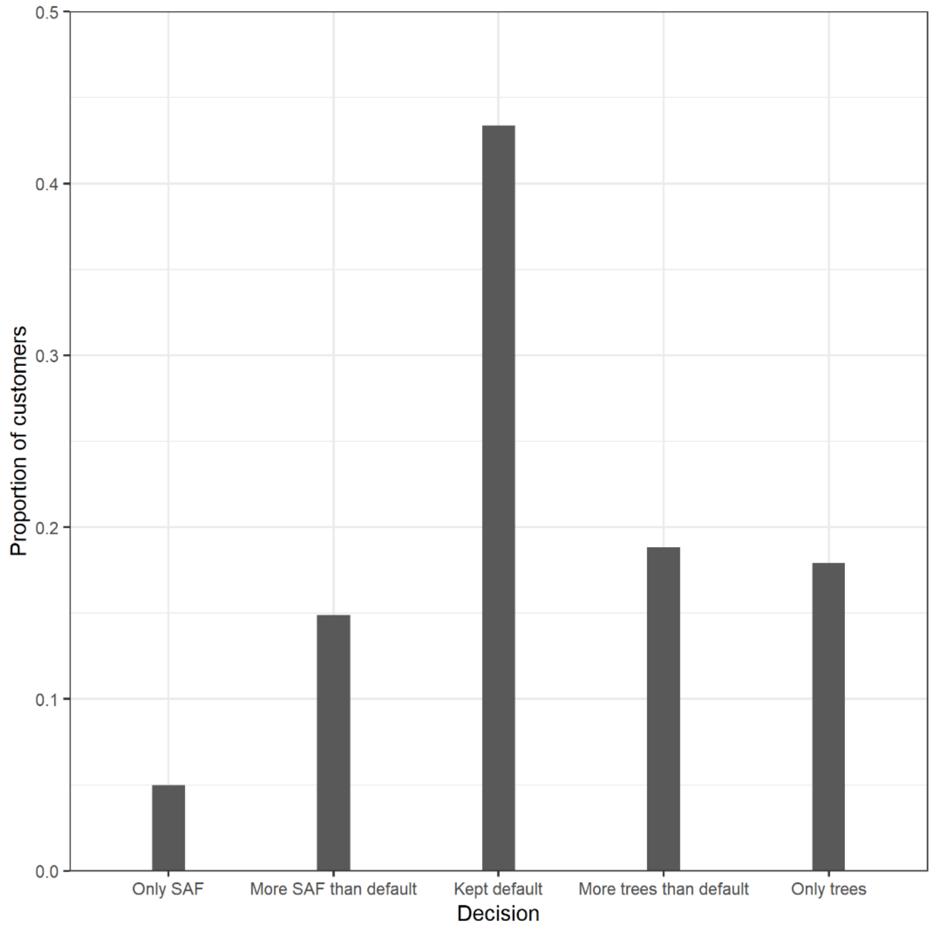
This file includes:

Supplementary Figures 1 to 10
Supplementary Tables 1 to 15

Other Supplementary Materials for this manuscript include the following:

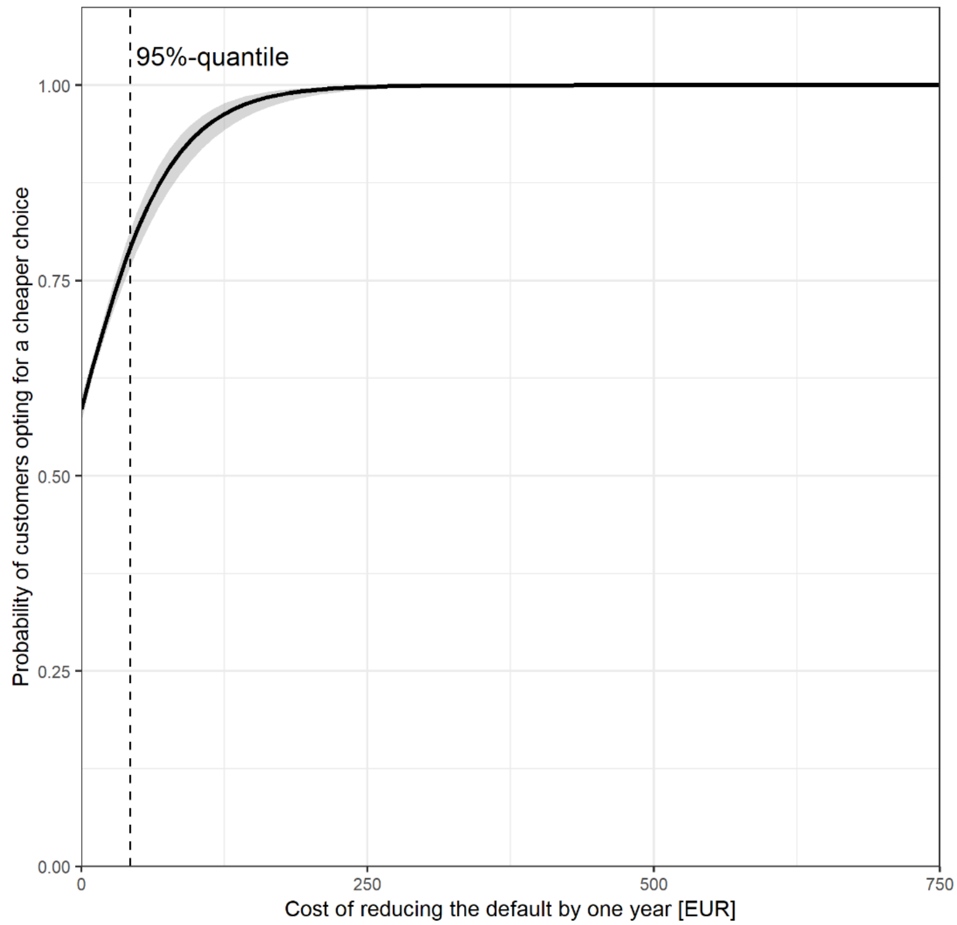
Additional References

Supplementary Figure 1. *Histogram of decisions*



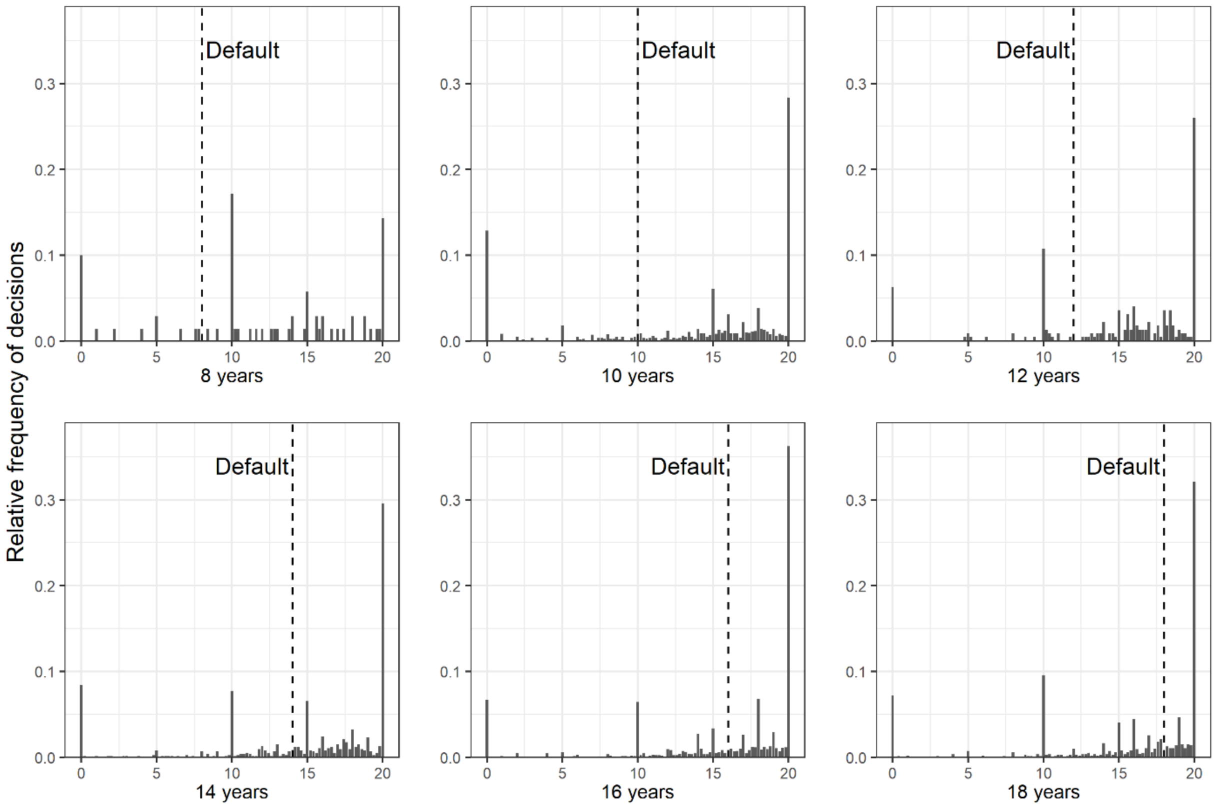
Notes: The Figure displays the proportions of customers sticking to the default, choosing to purchase the cheapest (i.e., only trees) and most expensive (i.e., only SAF) options as well as those who deviated from the default but did not opt for a boundary option (either moving towards more SAF or more trees from the default). Note that only the outermost groups share the same decision while the particular choices can vary for the middle groups (e.g., deciding on 12 years to offset can constitute more SAF than default if the default for this customer was set above 12 years, sticking to the default if the default was set to 12 years, or more trees than default if the default was set below 12 years).

Supplementary Figure 2. *Logit regression line (including 95% confidence interval) of the probability to move to a cheaper offset, i.e. more trees, on the cost of one year less to offset (only considering customers who deviated from the default)*



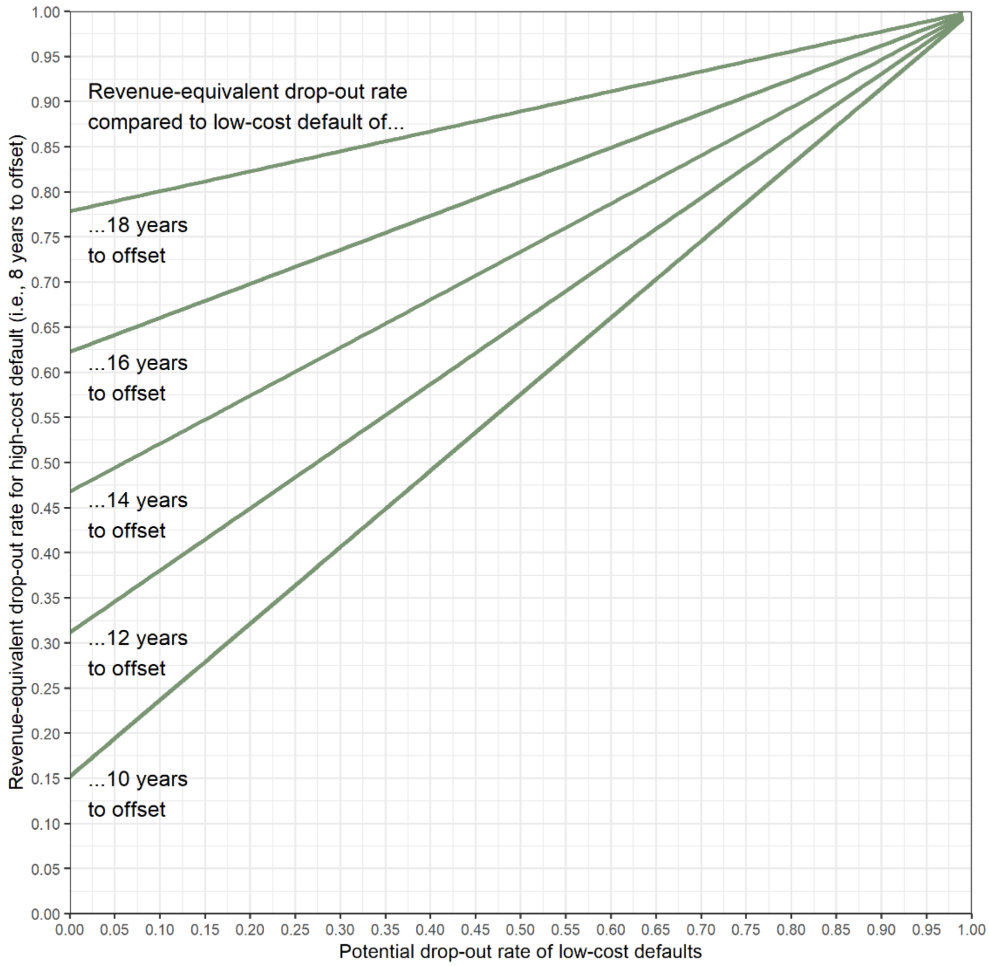
Notes: This depiction shows the steep increase in likelihood of moving to a cheaper option when the cost of reducing the time to offset increases. For very high-cost compensation decisions, virtually no one chooses more expensive options.

Supplementary Figure 3. *Relative frequencies of all chosen years for each default value (only considering customers who deviated from the default)*



Notes: Supplementary Figure 3 shows that a much higher share of those customers not sticking to the default moved to a cheaper option. Additionally, it shows that for all but the most expensive default the majority of moving customers chose the cheapest option (i.e., 20 years to offset).

Supplementary Figure 4. *Sensitivity analysis of drop-out rates for high-cost default*



Notes: Supplementary Figure 4 displays drop-out rates for high-cost default (i.e., 8 years to offset) yielding the same revenue as the respective potential drop-out rates for the different lower-cost defaults. For example, if the 12-year-default would lead to a drop-out rate of 5%, the 8-year-default would yield at least the same revenue as long as its drop-out rate would not exceed 19.7%. The same approach applies to the other defaults and potential drop-out rates (see further explanation and calculation steps below). Note that high-cost defaults are not more costly across participants but more costly from a “within-subject” perspective.

Encountering an expensive initial slider position when entering the offsetting platform might lead to an increased number of customers leaving the platform without purchasing any compensation. As the platform does not systematically track these drop-out rates, we conducted a sensitivity analysis to understand which drop-out rates of the high-cost default (i.e., 8 years to offset) yield at least the same revenue compared to any given potential drop-out rate of the other (i.e., lower-cost) defaults. We use the formula below to calculate the revenue for all defaults (per kg CO2-eq.):

$$\boldsymbol{Revenue_{per\ kgCO_2eq} = (1 - DropOutRate) * Price_{per\ kgCO_2eq}}$$

Given the high proportions of customers sticking to the default for all default values (see Figure 2) we assume the expected revenue per kg CO2-eq. is very close to the price level exactly on the default (and does not systematically differ across defaults). Thus, the drop-out rate in the high-cost default scenario (HC) that would yield (at least) the same revenue as the low-cost default (LC) is given by the following formula (as a function of the drop-out rate in the low-cost default scenario):

$$\boldsymbol{Revenue_{per\ kgCO_2eq,LC} \stackrel{\text{def}}{=} Revenue_{per\ kgCO_2eq,HC}} \Leftrightarrow$$

$$\boldsymbol{Revenue_{per\ kgCO_2eq,LC} = (1 - DropOutRate_{HC}) * Price_{per\ kgCO_2eq,HC}} \Leftrightarrow$$

$$\boldsymbol{DropOutRate_{HC} = 1 - \frac{Revenue_{LC}}{Price_{per\ kgCO_2eq,HC}}} \Leftrightarrow$$

$$\boldsymbol{DropOutRate_{HC} = 1 - \frac{(1 - DropOutRate_{LC}) * Price_{per\ kgCO_2eq,LC}}{Price_{per\ kgCO_2eq,HC}}}$$

Supplementary Table 1. Linear regressions of offsetting decisions in years to offset on default encountered without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3) for all customers who deviated from the default.

	Model 1			**Model 2**			**Model 3**		
Variable	*B*	*CI*	*p*	*B*	*CI*	*p*	*B*	*CI*	*p*
Intercept	13.54	13.21 – 13.88	**<0.001**	14.41	13.98 – 14.84	**<0.001**	13.31	12.52 – 14.09	**<0.001**
Default	0.44	0.34 – 0.53	**<0.001**	0.28	0.19 – 0.38	**<0.001**	0.57	0.38 – 0.76	**<0.001**
CO2 emissions [metric tons]				1.04	0.85 – 1.24	**<0.001**	0.72	0.39 – 1.06	**<0.001**
Number of trips				0.06	0.00 – 0.12	**0.041**	0.29	0.17 – 0.42	**<0.001**
Non-eco flights (1 = min. one non-eco flight)				-0.64	-0.93 – -0.36	**<0.001**	-0.54	-1.05 – -0.02	**0.041**
Gender (1 = female)							0.28	-0.24 – 0.79	0.290
Business travel							-0.78	-1.44 – -0.12	**0.020**
Sub-platform controls	No			Yes			Yes		
Observations	6318			6318			2309		
R^2 / R^2 adjusted	0.012 / 0.012			0.063 / 0.062			0.079 / 0.075		

Note: Table displays unstandardized coefficients (*B*) with 95%-confidence intervals (*CI*) and *p*-values of t-tests (*p*) from linear regressions with years to full offset as the dependent variable. Bold *p*-values indicate significance at the 0.05-level. Default is entered as a continuous variable ranging from 0 (8 years) to 5 (18 years). Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 1 shows that even customers who decide to move away from the default they are exposed to are significantly impacted by the default in their decision. When encountering the next higher defaults, these customers choose ceteris paribus between 0.28 and 0.57 more years to offset depending on the model specifications. This result is robust to controlling for various transaction-level and customer characteristics (Models 2 and 3). Models 2 and 3 also show, however, that other factors exert a strong influence on the customers' decisions. Namely, higher emissions lead to choices of longer offsets. On the other hand, customers booking any higher class than economy and business travellers choose shorter offsetting times. The effect of the number of trips is – even though it reaches statistical significance – negligible as the vast majority of customers (70.80%) compensate no more than two trips (i.e., two flights with one passenger each or two passengers on one flight). The customer's gender has no significant impact on her decision. Supplementary Table 2 presents the identical analyses using robust standard errors.

Supplementary Table 2. Linear regressions (with robust standard errors) of offsetting decisions in years to offset on default encountered without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3) for all customers who deviated from the default.

	Model 1				**Model 2**				**Model 3**			
Variable	*B*	*SE*	*CI*	*p*	*B*	*SE*	*CI*	*p*	*B*	*SE*	*CI*	*p*
Intercept	13.54	0.19	13.18 – 13.91	**<0.001**	14.41	0.57	13.30 – 15.52	**<0.001**	13.31	0.43	12.46 – 14.16	**<0.001**
Default	0.44	0.05	0.33 – 0.54	**<0.001**	0.28	0.06	0.17 – 0.40	**<0.001**	0.57	0.10	0.36 – 0.77	**<0.001**
CO2 emissions [metric tons]					1.04	0.16	0.74 – 1.35	**<0.001**	0.72	0.20	0.34 – 1.11	**<0.001**
Number of trips					0.06	0.19	-0.31 – 0.43	0.748	0.29	0.06	0.18 – 0.41	**<0.001**
Non-eco flights (1 = min. one non-eco booking)					-0.64	0.18	-0.99 – -0.29	**<0.001**	-0.54	0.27	-1.06 – -0.01	**0.045**
Gender (1 = female)									0.28	0.25	-0.22 – 0.77	0.274
Business travel									-0.78	0.36	-1.50 – -0.07	**0.031**
Sub-platform controls	No				Yes				Yes			
Observations	6318				6318				2309			
R^2 / R^2 adjusted	0.012 / 0.012				0.063 / 0.062				0.079 / 0.075			

Note: Table displays unstandardized coefficients (*B*) and standard errors estimated using the heteroskedasticity-consistent covariance matrix estimation "HC3" (*SE*) with 95%-confidence intervals (*CI*) and *p*-values of t-tests (*p*) from linear regressions with years to full offset as the dependent variable. Bold *p*-values indicate significance at the 0.05-level. Default is entered as a continuous variable ranging from 0 (8 years) to 5 (18 years). Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 3. Tobit regressions (lower limit = 0, upper limit = 20) of offsetting decisions in years to offset on default encountered without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3) for all customers who deviated from the default.

	Model 1			Model 2			Model 3		
Variable	*B*	*CI*	*p*	*B*	*CI*	*p*	*B*	*CI*	*p*
Intercept	14.52	13.97 – 15.06	**<0.001**	16.26	15.56 – 16.95	**<0.001**	14.13	12.89 – 15.36	**<0.001**
Default	0.67	0.52 – 0.83	**<0.001**	0.33	0.17 – 0.49	**<0.001**	0.75	0.45 – 1.04	**<0.001**
CO2 emissions [metric tons]				2.59	2.19 – 2.98	**<0.001**	1.77	1.17 – 2.37	**<0.001**
Number of trips				-0.04	-0.14 – 0.06	0.434	0.51	0.29 – 0.72	**<0.001**
Non-eco flights (1 = min. one non-eco flight)				-0.97	-1.44 – -0.49	**<0.001**	-0.98	-1.82 – -0.15	**0.021**
Gender (1 = female)							0.07	-0.73 – 0.87	0.862
Business travel							-1.18	-2.20 – -0.17	**0.023**
Sub-platform controls	No			Yes			Yes		
Observations	6318			6318			2309		
R^2 Nagelkerke	0.011			0.075			0.090		

Note: Table displays unstandardized coefficients (*B*) with 95%-confidence intervals (*CI*) and *p*-values of t-tests (*p*) from tobit regressions (lower limit = 0, upper limit = 20) with years to full offset as the dependent variable. Bold *p*-values indicate significance at the 0.05-level. Default is entered as a continuous variable ranging from 0 (8 years) to 5 (18 years). Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 3 shows the results in Supplementary Table 1 are robust to accounting for the censored structure of the dependent variable (i.e., customers could only choose offsetting durations between 0 and 20 years) by employing tobit regression models. None of the substantial results explained above qualitatively change when comparing the linear regressions to the tobit regressions. Supplementary Table 4 presents the identical analyses using robust standard errors.

Supplementary Table 4. Tobit regressions (lower limit = 0, upper limit = 20; with robust standard errors) of offsetting decisions in years to offset on default encountered without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3) for all customers who deviated from the default.

	Model 1				Model 2				Model 3			
Variable	*B*	*SE*	*CI*	*p*	*B*	*SE*	*CI*	*p*	*B*	*SE*	*CI*	*p*
Intercept	14.52	0.29	13.96 – 15.08	**<0.001**	16.26	0.66	14.97 – 17.55	**<0.001**	14.13	0.67	12.81 – 15.45	**<0.001**
Default	0.67	0.08	0.51 – 0.83	**<0.001**	0.33	0.09	0.15 – 0.51	**<0.001**	0.75	0.16	0.43 – 1.06	**<0.001**
CO2 emissions [metric tons]					2.59	0.30	1.99 – 3.18	**<0.001**	1.77	0.45	0.89 – 2.65	**<0.001**
Number of trips					-0.04	0.20	-0.43 – 0.35	0.842	0.51	0.11	0.29 – 0.72	**<0.001**
Non-eco flights (1 = min. one non-eco booking)					-0.97	0.29	-1.54 – -0.39	**0.001**	-0.98	0.44	-1.85 – -0.12	**0.026**
Gender (1 = female)									0.07	0.39	-0.69 – 0.83	0.856
Business travel									-1.18	0.54	-2.24 – -0.13	**0.028**
Sub-platform controls	No				Yes				Yes			
Observations	6318				6318				2309			
R^2 Nagelkerke	0.011				0.075				0.090			

Note: Table displays unstandardized coefficients (*B*) and standard errors estimated using the heteroskedasticity-consistent covariance matrix estimation "HC0" (*SE*) with 95%-confidence intervals (*CI*) and *p*-values of t-tests (*p*) from tobit regressions (lower limit = 0, upper limit = 20) with years to full offset as the dependent variable. Bold *p*-values indicate significance at the 0.05-level. Default is entered as a continuous variable ranging from 0 (8 years) to 5 (18 years). Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 5. Logit regressions of decision to keep the default on default encountered without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3).

	Model 1			Model 2			Model 3		
Variable	*OR*	*CI*	*p*	*OR*	*CI*	*p*	*OR*	*CI*	*p*
Intercept	0.42	0.35 – 0.50	**<0.001**	0.51	0.45 – 0.58	**<0.001**	0.35	0.28 – 0.43	**<0.001**
Default	1.09	1.06 – 1.11	**<0.001**	1.15	1.12 – 1.18	**<0.001**	1.13	1.07 – 1.19	**<0.001**
CO2 emissions [metric tons]				0.70	0.65 – 0.76	**<0.001**	0.77	0.67 – 0.88	**<0.001**
Number of trips				0.98	0.96 – 1.01	0.161	1.00	0.96 – 1.04	0.888
Non-eco flights (1 = min. one non-eco flight)				1.01	0.93 – 1.10	0.755	1.00	0.85 – 1.18	0.964
Gender (1 = female)							1.57	1.37 – 1.80	**<0.001**
Business travel							1.31	1.10 – 1.57	**0.003**
Sub-platform controls	No			Yes			Yes		
Observations	11159			11159			3885		
R^2 Tjur	0.004			0.039			0.042		

Note: Table displays odds ratios (*OR*) with 95%-confidence intervals (*CI*) and *p*-values of t-tests (*p*) from logit regressions with decision to keep the default (deviating as base) as the dependent variable. Bold *p*-values indicate significance at the 0.05-level. Default is entered as a continuous variable ranging from 0 (8 years) to 5 (18 years). Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 5 shows that higher (and thus cheaper) defaults increase the likelihood of customers sticking to the default. This result is robust to controlling for various transaction-level and customer characteristics (Models 2 and 3). Models 2 and 3 also show that higher emissions (which lead to a higher cost level, all else equal) reduce the likelihood of the default being kept. Additionally, female customers and business travellers are more likely to keep the default. Supplementary Table 6 presents the identical analyses using robust standard errors.

Supplementary Table 6. Logit regressions (with robust standard errors) of decision to keep the default on default encountered without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3).

	Model 1				Model 2				Model 3			
Variable	*OR*	*SE*	*CI*	*p*	*OR*	*SE*	*CI*	*p*	*OR*	*SE*	*CI*	*p*
Intercept	0.42	0.04	0.35 – 0.50	**<0.001**	0.51	0.03	0.45 – 0.58	**<0.001**	0.35	0.04	0.28 – 0.43	**<0.001**
Default	1.09	0.01	1.06 – 1.11	**<0.001**	1.15	0.01	1.12 – 1.18	**<0.001**	1.13	0.03	1.07 – 1.19	**<0.001**
CO2 emissions [metric tons]					0.70	0.03	0.64 – 0.76	**<0.001**	0.77	0.05	0.67 – 0.89	**<0.001**
Number of trips					0.98	0.01	0.96 – 1.01	0.155	1.00	0.02	0.96 – 1.04	0.888
Non-eco flights (1 = min. one non-eco booking)					1.01	0.04	0.93 – 1.10	0.758	1.00	0.08	0.86 – 1.17	0.962
Gender (1 = female)									1.57	0.11	1.37 – 1.80	**<0.001**
Business travel									1.31	0.12	1.10 – 1.57	**0.003**
Sub-platform controls			No				Yes				Yes	
Observations	11159				11159				3885			
R^2 Tjur	0.004				0.039				0.042			

Note: Table displays odds ratios (*OR*) and standard errors estimated using the heteroskedasticity-consistent covariance matrix estimation "HC3" (*SE*) with 95%-confidence intervals (*CI*) and *p*-values of t-tests (*p*) from logit regressions with decision to keep the default (deviating as base) as the dependent variable. Bold *p*-values indicate significance at the 0.05-level. Default is entered as a continuous variable ranging from 0 (8 years) to 5 (18 years). Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 7. Logit regressions of decision to keep the default on cost of keeping the default without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3).

	Model 1			**Model 2**			**Model 3**		
Variable	*OR*	*CI*	*p*	*OR*	*CI*	*p*	*OR*	*CI*	*p*
Intercept	0.98	0.93 – 1.03	0.446	0.80	0.73 – 0.88	**<0.001**	0.48	0.40 – 0.58	**<0.001**
Cost of default [EUR]	0.99	0.99 – 1.00	**<0.001**	0.99	0.99 – 0.99	**<0.001**	0.99	0.99 – 0.99	**<0.001**
CO2 emissions [metric tons]				1.33	1.19 – 1.49	**<0.001**	1.57	1.25 – 1.97	**<0.001**
Number of trips				1.02	0.99 – 1.04	0.206	1.04	1.00 – 1.09	0.060
Non-eco flights (1 = min. one non-eco flight)				1.02	0.94 – 1.11	0.596	1.05	0.88 – 1.24	0.575
Gender (1 = female)							1.59	1.38 – 1.82	**<0.001**
Business travel							1.27	1.06 – 1.51	**0.010**
Sub-platform controls	No			Yes			Yes		
Observations	11159			11159			3885		
R^2 Tjur	0.019			0.040			0.046		

Note: Table displays odds ratios (*OR*) with 95%-confidence intervals (*CI*) and *p*-values of t-tests (*p*) from logit regressions with decision to keep the default (deviating as base) as the dependent variable. Bold *p*-values indicate significance at the 0.05-level. Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 7 shows that a higher cost of the default (compared to the cheapest available alternative) reduces the likelihood of customers sticking to the default. This result is robust to controlling for various transaction-level and customer characteristics (Models 2 and 3). Interestingly, Models 2 and 3 also show that higher emissions in this case (i.e., when controlling for the cost level) increase the likelihood of the default being kept. Additionally, female customers and business travellers are more likely to keep the default. Supplementary Table 8 presents the identical analyses using robust standard errors.

Supplementary Table 8. Logit regressions (with robust standard errors) of decision to keep the default on cost of keeping the default without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3).

	Model 1				**Model 2**				**Model 3**			
Variable	*OR*	*SE*	*CI*	*p*	*OR*	*SE*	*CI*	*p*	*OR*	*SE*	*CI*	*p*
Intercept	0.98	0.03	0.93 – 1.04	0.479	0.80	0.04	0.73 – 0.88	**<0.001**	0.48	0.05	0.40 – 0.58	**<0.001**
Cost of default [EUR]	0.99	0.00	0.99 – 1.00	**<0.001**	0.99	0.00	0.99 – 0.99	**<0.001**	0.99	0.00	0.99 – 0.99	**<0.001**
CO2 emissions [metric tons]					1.33	0.08	1.19 – 1.49	**<0.001**	1.57	0.21	1.20 – 2.05	**0.001**
Number of trips					1.02	0.01	0.99 – 1.04	0.218	1.04	0.02	1.00 – 1.09	0.069
Non-eco flights (1 = min. one non-eco booking)					1.02	0.04	0.94 – 1.11	0.594	1.05	0.09	0.89 – 1.23	0.555
Gender (1 = female)									1.59	0.11	1.38 – 1.82	**<0.001**
Business travel									1.27	0.12	1.06 – 1.52	**0.010**
Sub-platform controls	No				Yes				Yes			
Observations	11159				11159				3885			
R^2 Tjur	0.019				0.040				0.046			

Note: Table displays odds ratios (*OR*) and standard errors estimated using the heteroskedasticity-consistent covariance matrix estimation "HC3" (*SE*) with 95%-confidence intervals (*CI*) and *p*-values of t-tests (*p*) from logit regressions with decision to keep the default (deviating as base) as the dependent variable. Bold *p*-values indicate significance at the 0.05-level. Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 9. Logit regressions of deviation direction (deviation towards shorter time to offset, i.e. more SAF, as base) on cost of reducing the default by one year without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3) for all customers who deviated from the default.

	Model 1			**Model 2**			**Model 3**		
Variable	*OR*	*CI*	*p*	*OR*	*CI*	*p*	*OR*	*CI*	*p*
Intercept	1.40	1.31 – 1.50	**<0.001**	1.61	1.41 – 1.84	**0.018**	2.21	1.71 – 2.87	0.142
Cost of default [EUR]	1.02	1.02 – 1.03	**<0.001**	1.02	1.01 – 1.02	**<0.001**	1.01	1.01 – 1.02	**0.001**
Number of trips				1.12	1.09 – 1.16	**<0.001**	1.15	1.08 – 1.23	**<0.001**
Non-eco flights (1 = min. one non-eco flight)				0.81	0.73 – 0.90	**<0.001**	0.73	0.60 – 0.89	**0.002**
Gender (1 = female)							1.04	0.86 – 1.26	0.698
Business travel							0.80	0.63 – 1.02	0.070
Sub-platform controls	No			Yes			Yes		
Observations	6318			6318			2309		
R^2 Tjur	0.027			0.051			0.048		

Note: Table displays odds ratios (*OR*) with 95%-confidence intervals (*CI*) and p-values of t-tests (*p*) from logit regressions with deviation direction (moving towards shorter time to offset, i.e. more SAF, as base) as the dependent variable. Bold p-values indicate significance at the 0.05-level. Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 9 shows that among customers who deviated from the default, a higher cost of reducing the default by one year increases the likelihood of customers moving towards a cheaper choice (versus a more expensive one). This result is robust to controlling for various transaction-level and customer characteristics (Models 2 and 3). Customers who purchased compensation for more trips also tended to move towards cheaper choices, whereas customers with at least one non-economy class booking in the set they purchased compensation for rather moved to more expensive choices. The customer's gender and the type of trip (business or private) have no significant influence on the decision. Supplementary Table 10 presents the identical analyses using robust standard errors.

Supplementary Table 10: Logit regressions (with robust standard errors) of deviation direction (deviation towards shorter time to offset, i.e. more SAF, as base) on cost of reducing the default by one year without controls (Model 1), with booking-related controls (Model 2) and with all controls (Model 3) for all customers who deviated from the default.

	Model 1				**Model 2**				**Model 3**			
Variable	*OR*	*SE*	*CI*	*p*	*OR*	*SE*	*CI*	*p*	*OR*	*SE*	*CI*	*p*
Intercept	1.40	0.05	1.30 – 1.51	**<0.001**	1.61	0.12	1.40 – 1.86	**<0.001**	2.21	0.31	1.69 – 2.90	**<0.001**
Cost of default [EUR]	1.02	0.00	1.02 – 1.03	**<0.001**	1.02	0.00	1.01 – 1.02	**<0.001**	1.01	0.00	1.00 – 1.02	**0.003**
Number of trips					1.12	0.02	1.08 – 1.17	**<0.001**	1.15	0.04	1.08 – 1.23	**<0.001**
Non-eco flights (1 = min. one non-eco booking)					0.81	0.04	0.73 – 0.90	**<0.001**	0.73	0.07	0.60 – 0.89	**0.002**
Gender (1 = female)									1.04	0.10	0.85 – 1.26	0.699
Business travel									0.80	0.10	0.63 – 1.02	0.072
Sub-platform controls	No				Yes				Yes			
Observations	6318				6318				2309			
R^2 Tjur	0.027				0.051				0.048			

Note: Table displays odds ratios (*OR*) and standard errors estimated using the heteroskedasticity-consistent covariance matrix estimation “HC3” (*SE*) with 95%-confidence intervals (*CI*) and p-values of t-tests (*p*) from logit regressions with deviation direction (moving towards shorter time to offset, i.e. more SAF, as base) as the dependent variable. Bold p-values indicate significance at the 0.05-level. Sub-platform controls are dummies indicating whether the transaction was made through the booking platforms of one of the airlines, the staff booking tool, or the compensation platform directly. Information on gender and type of travel is only available for a subset of the customers. P-values refer to two-sided tests.

Supplementary Table 11. Percentage of customers that kept the default, grouped by the cost of keeping the default (compared to the cheapest possible option).

	Total no. of customers	**% who kept the default**
< 16 EUR	2,140	52.06
16 - 25 EUR	2,638	48.64
26 - 50 EUR	3,281	41.73
51 - 100 EUR	1,807	39.24
101-200 EUR	933	31.73
201-300 EUR	227	21.59
301-400 EUR	60	13.33
401-500 EUR	33	12.12
501-600 EUR	17	17.65
601-700 EUR	10	40
701-800 EUR	5	40

Supplementary Table 11 shows that the proportion of customers who are keeping the default declines with increased cost of the default (compared to the cheapest available option).

Results using propensity score matching (see methods of the main text)

As there the covariates differed between the different default levels, we applied a propensity score matching using the package MatchIt (Stuart et al., 2011) in R. MatchIt follows the suggestions of Ho et al. (2007) for improving parametric statistical models and reducing model dependence by preprocessing data with different matching methods. More specifically, we used optimal pair matching that attempts to pair each "treated" unit with one or more control units. In other words, we matched participants who were presented a default of 8 years with participants who were presented a different default based on the CO_2 emission that was attached to their off-setting choice. We first used the level of CO_2 emission as our relevant covariate as it is showed substantial differences between the default levels. Based on the new subset ($n_{matched\ data} = 678$), we again present the behavioural "stickiness" to the pre-selected default settings for each of the six default values employed in the field study (see Fig. S8).

Supplementary Table 12 shows the mean CO_2 emissions prior to and after the matching procedure. Altough the ANOVA also yielded a significant effect in the matched data set ($p = 0.022$), the differences of CO_2 emissions between the defaults have strongly decreased (see Fig. S5). The differences of mean number of trips between defaults also remained statistically significant after the matching procedure ($p < 0.001$, see Supplementary Table 13 and Supplementary Figure 6), but differences of mean non-economy flights were no longer significant ($p = 0.178$, see also Supplementary Table 14 and Supplementary Figure 7). Supplementary Figure 8 shows that the there is a strong behavioural "stickiness" to the pre-selected default settings for each of the six default even after the matching procedure.

Next, we matched participants who were presented a default of 8 years with participants who were presented a different default based on the cost of keeping the default (see

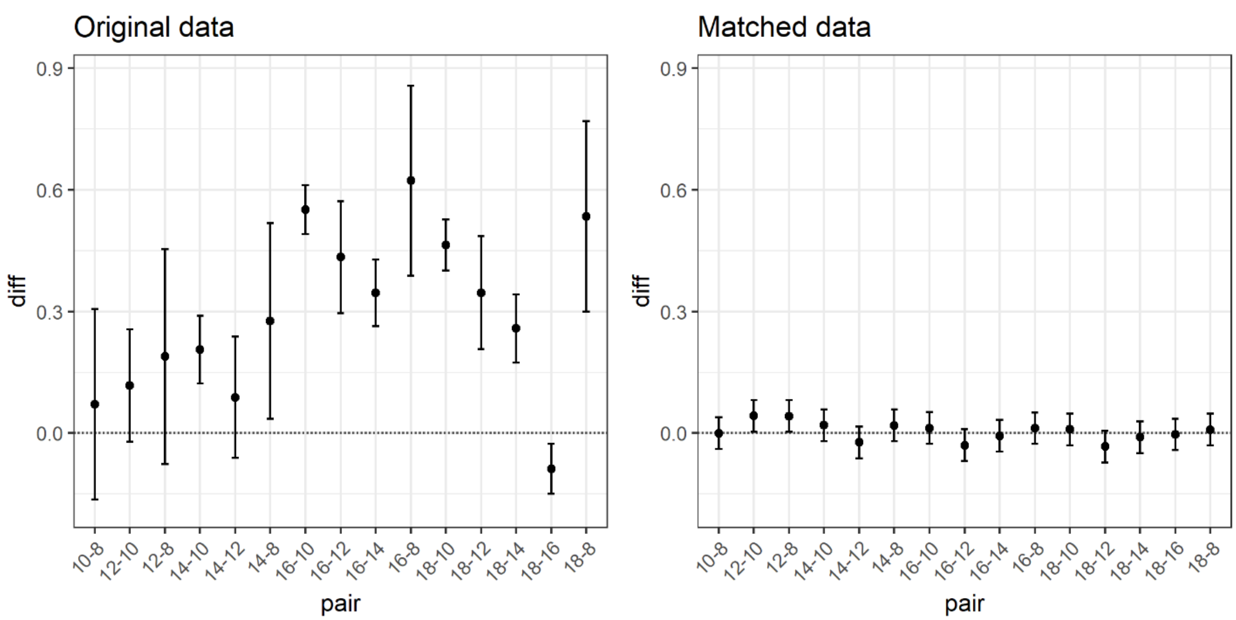
Supplementary Table 15 and Supplementary Figure 9). Supplementary Figure 10 again shows that the there is a strong behavioural "stickiness" to the pre-selected default settings also in the subsample matched for cost of switching the default. Together, these results indicate that indicating that the default effect was not driven by a systematic bias.

Supplementary Table 12. *Mean CO_2 emissions per default with ANOVA results*

	Original data				Matched data			
Default	*M (SD)*	*df*	*F*	*p*	*M(SD)*	*df*	*F*	*p*
8	0.12 (0.07)				0.12 (0.07)			
10	0.19 (0.16)				0.12 (0.07)			
12	0.31 (0.24)	5	165.90	<.001	0.16 (0.07)	5	2.66	0.022
14	0.40 (0.61)				0.14 (0.06)			
16	0.74 (1.24)				0.13 (0.15)			
18	0.66 (0.90)				0.13 (0.14)			

Notes: $n_{original\ data} = 11,159$, $n_{matched\ data} = 678$.

Supplementary Figure 5. *Differences of CO2 emissions between defaults*

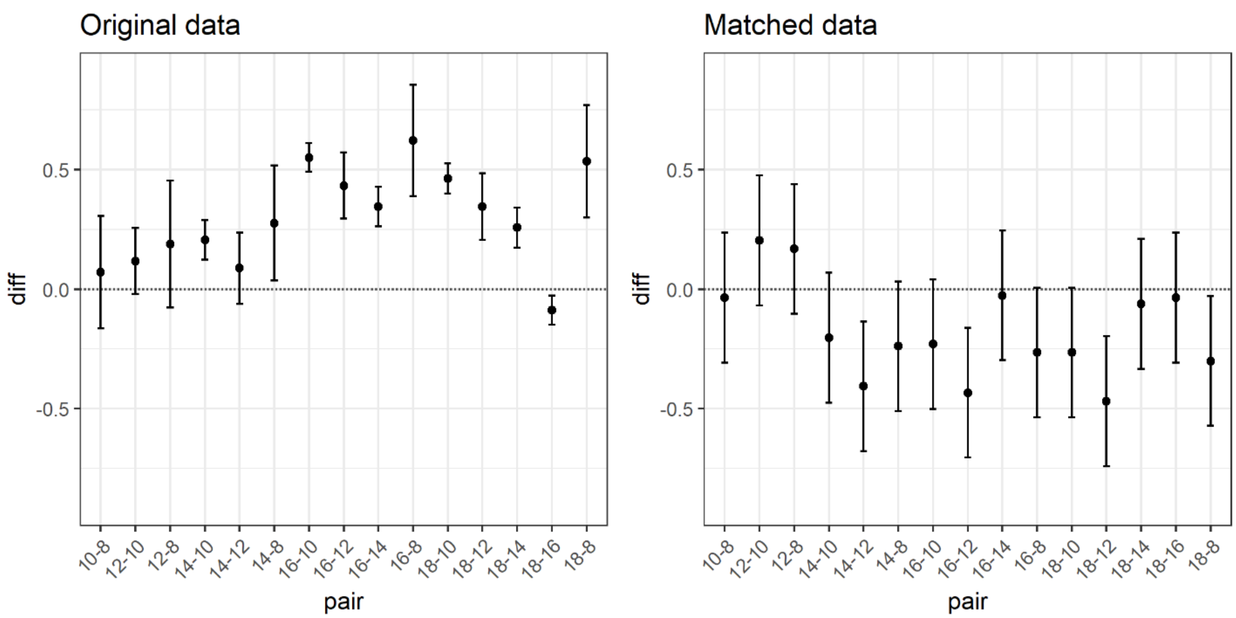


Supplementary Table 13. *Mean number of trips per default with ANOVA results*

	Original data				*Matched data*			
Default	*M (SD)*	*df*	*F*	*P*	*M(SD)*	*df*	*F*	*p*
8	1.65 (0.89)				1.65 (0.90)			
10	2.43 (1.93)				1.62 (0.83)			
12	2.89 (1.81)	5	15.89	<.001	1.82 (0.70)	5	7.63	<.001
14	2.92 (1.81)				1.42 (0.64)			
16	2.88 (3.76)				1.39 (0.59)			
18	2.83 (2.25)				1.35 (0.58)			

Notes: $n_{original\ data} = 11{,}159$, $n_{matched\ data} = 678$.

Supplementary Figure 6. *Differences of mean number of trips between defaults*

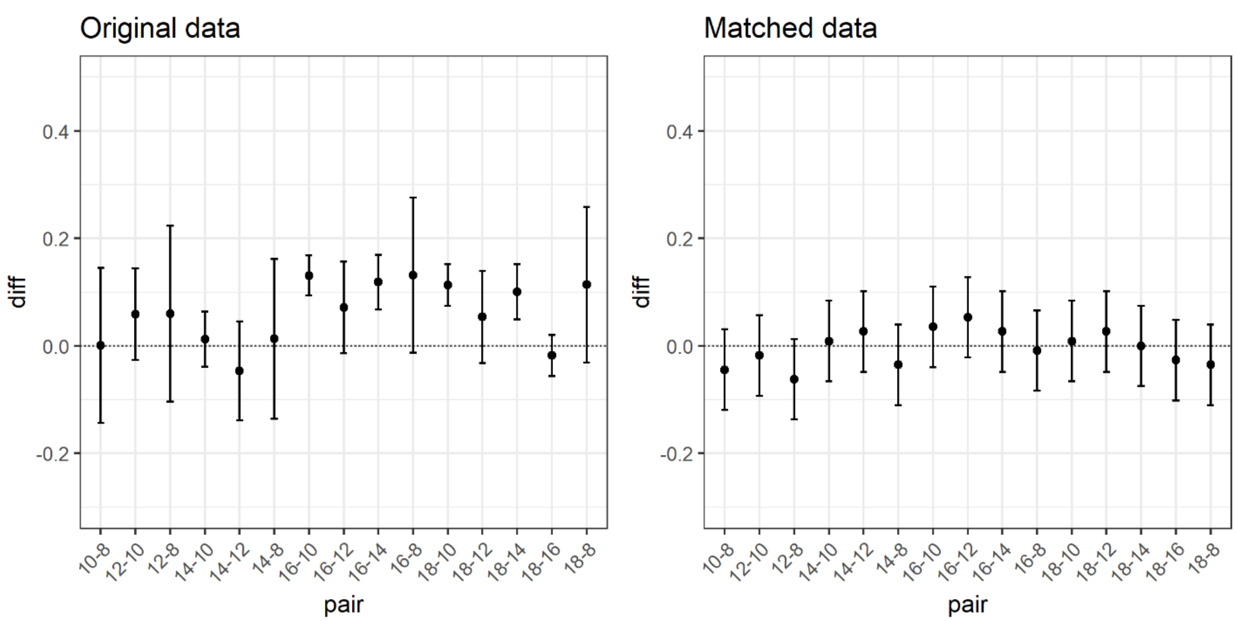


Supplementary Table 14. *Mean number of non-eco flights per default with ANOVA results*

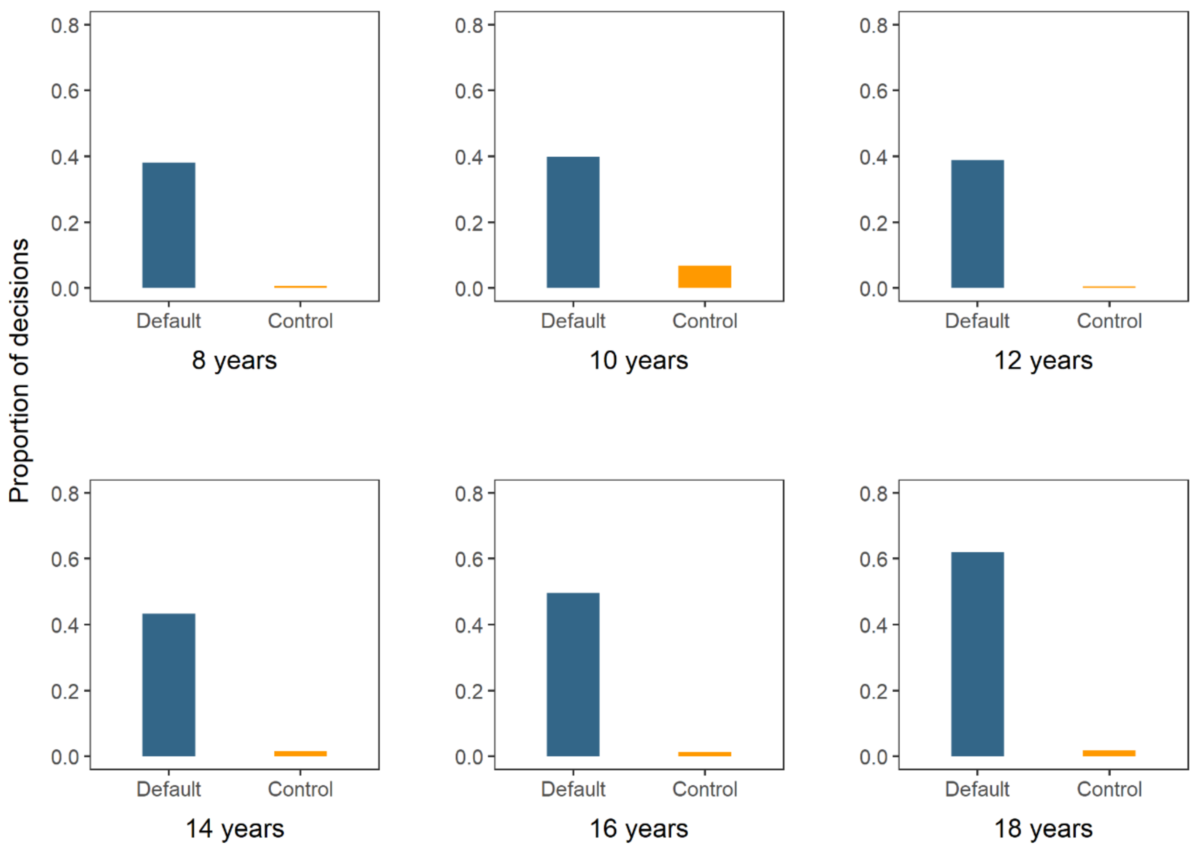
Default	*Original data*				*Matched data*			
	M (SD)	*df*	*F*	*p*	*M(SD)*	*df*	*F*	*p*
8	0.06 (0.28)	5	27.10	<.001	1.65 (0.90)	5	1.53	0.178
10	0.06 (0.35)				1.62 (0.83)			
12	0.12 (0.47)				1.82 (0.70)			
14	0.08 (0.41)				1.42 (0.64)			
16	0.19 (0.63)				1.39 (0.59)			
18	0.18 (0.62)				1.35 (0.58)			

Notes: $n_{original\ data} = 11{,}159$, $n_{matched\ data} = 678$.

Supplementary Figure 7. *Differences of mean number of non-eco flights between defaults*



Supplementary Figure 8: *Behavioral "stickiness" to the pre-selected default settings for each of six default values based on the propensity score matched data (for CO_2 emission levels)*



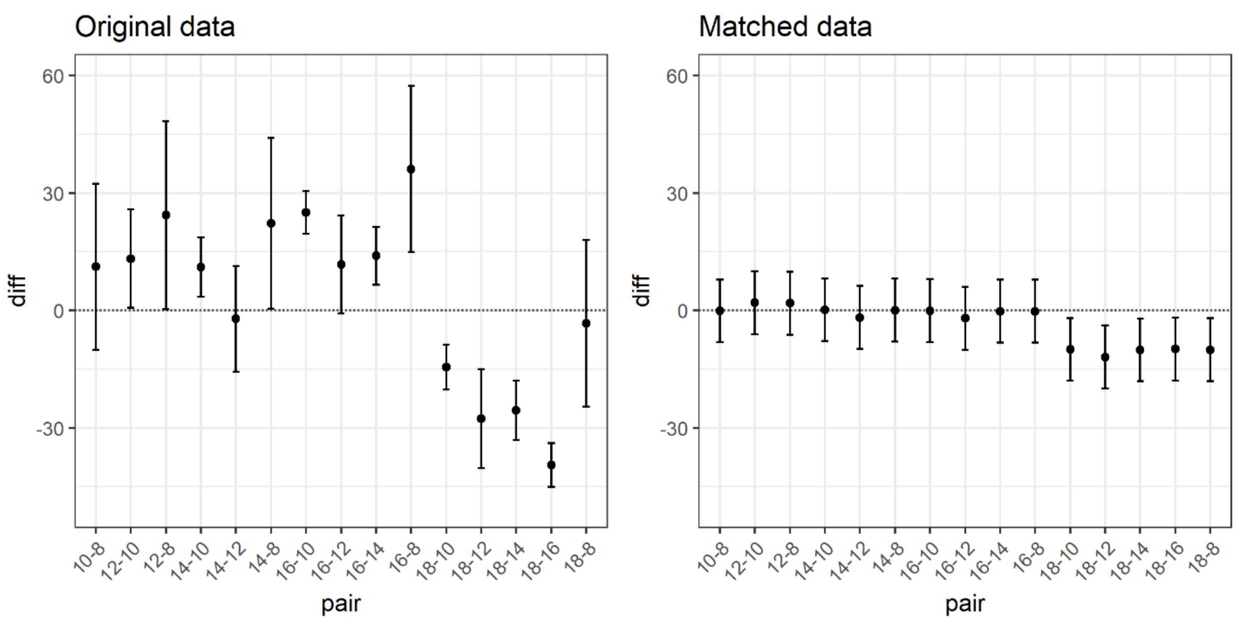
Note: The Figure displays the behavioural efficacy of the pre-selected default for each of the six default settings using propensity score matched data based on CO_2 emission levels (n = 678). Bars represent the share of decision-makers choosing the particular compensation scheme originating from the respective default (blue bars) and comparison groups (yellow bars). As in the main text, all tests of proportion (χ^2 tests, 1 df) are significant below the $p < 0.001$ level (8 years: $\chi^2(1)$= 197.81, 95% CI: 0.29-1; 10 years: $\chi^2(1)$= 91.01, 95% CI: 0.25-1; 12 years: $\chi^2(1)$= 209.39, 95% CI: 0.30-1; 14 years: $\chi^2(1)$= 204.72, 95% CI: 0.34-1; 16 years: $\chi^2(1)$= 255.14, 95% CI: 0.40-1; 18 years: $\chi^2(1)$= 321.91, 95% CI: 0.52-1). Note that the comparison group for each default consists of the entirety of customers exposed to the other five defaults (i.e. the web-design requires that the slider is positioned somewhere).

Supplementary Table 15. *Mean cost of keeping the default per default with ANOVA results*

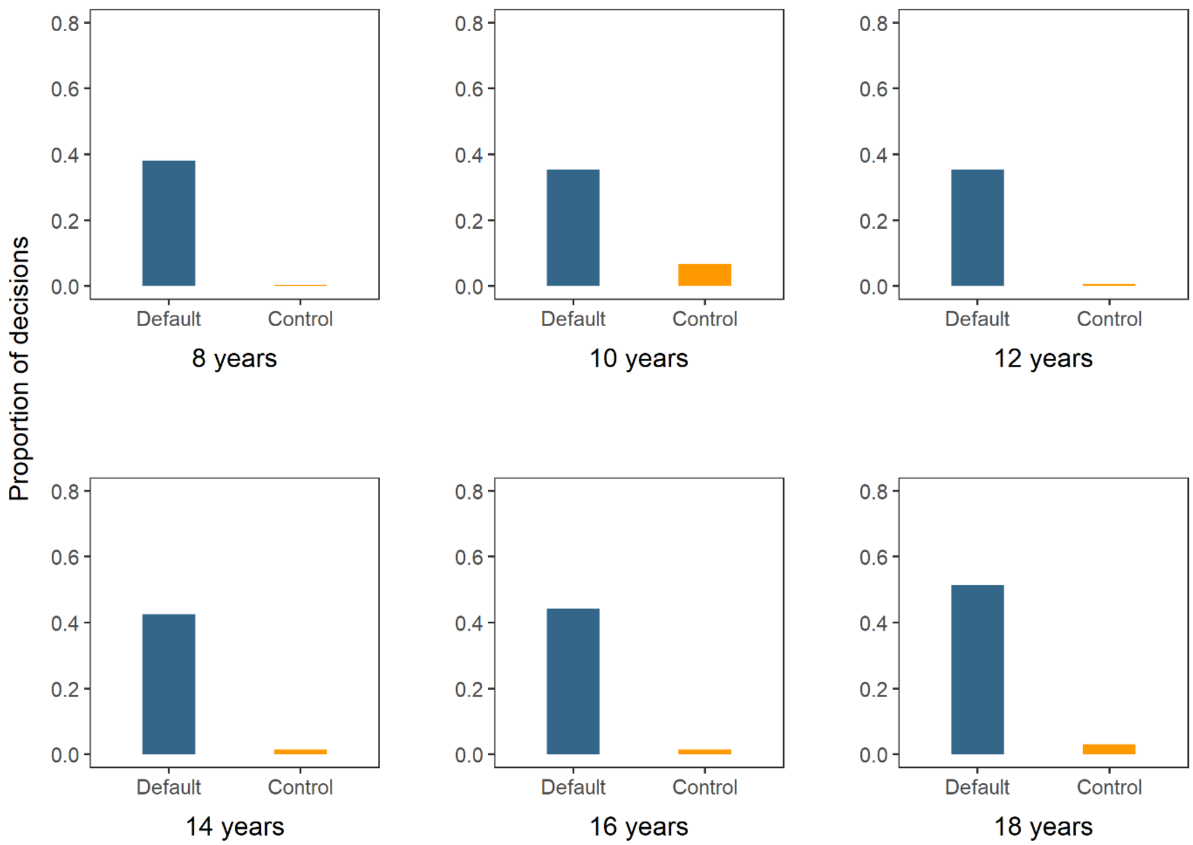
	Original data				*Matched data*			
Default	*M (SD)*	*df*	*F*	*p*	*M(SD)*	*df*	*F*	*p*
8	34.52 (20.37)				33.53 (20.37)			
10	45.66 (38.78)				34.41 (21.00)			
12	58.87 (44.73)	5	88.05	<.001	36.76 (19.24)	5	4.691	< 0.001
14	56.71 68.33)				34.56 (20.73)			
16	70.66 (117.51)				34.33 (20.71)			
18	31.17 (43.00)				24.46 (24.40)			

Notes: $n_{original\ data}$ = 11,159, $n_{matched\ data}$ = 678.

Supplementary Figure 9. *Differences of mean cost of keeping the default*



Supplementary Figure 10. *Behavioral "stickiness" to the pre-selected default settings for each of six default values based on the propensity score matched data (for costs of sticking with default)*



Note: The Figure displays the behavioural efficacy of the pre-selected default for each of the six default settings using propensity score matched data based on costs of sticking with default (n = 678). Bars represent the share of decision-makers choosing the particular compensation scheme originating from the respective default (blue bars) and control groups (yellow bars). As in the main text, all tests of proportion (χ^2 tests) are significant below the $p < 0.001$ level. (8 years: $\chi^2(1)=209.93$, 95% CI: 0.30-1.00; 10 years: $\chi^2(1)=73.25$, 95% CI: 0.21-1.00; 12 years: $\chi^2(1)=181.06$, 95% CI: 0.27-1.00; 14 years: $\chi^2(1)=204.15$, 95% CI: 0.27-1.00; 16 years: $\chi^2(1)=215.40$, 95% CI: 0.35-1.00; 18 years: $\chi^2(1)=218.58$, 95% CI: 0.40-1.00). Note that the comparison group for each default consists of the entirety of customers exposed to the other five defaults (i.e. the web-design requires that the slider is positioned somewhere).

References

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political analysis*, *15*(3), 199-236.

Stuart, E. A., King, G., Imai, K., & Ho, D. (2011). MatchIt: nonparametric preprocessing for parametric causal inference. *Journal of statistical software*.