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Sensitivity to Nudges: Does it Differ Across Generations?

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Abstract

Perhaps the world's greatest challenge today is climate change, mainly due to human causes. Nudging policies have shown promising results for behavioral improvement. However, little is known about generational differences in sensitivity to behavioral nudges. Understanding this would help in pursuing targeted policies that can have both effectiveness and cost benefits. This study aims to determine the generational differences between pre-millennials and millennials through an online experiment. Participants may or may not have been exposed to a nudge after which they donate a fictitious amount to an environmental charity. To see generational differences in sensitivity, the results of the nudge conditions are compared for both generations with their respective benchmark control group. The analysis concerns generational differences in both the amount donated and in the probability that a participant will donate at all after being exposed to certain condition. Although the results imply promising effects on millennials, they are contradictory and insignificant, which means that an unequivocal conclusion is not forthcoming until further research provides clarity.

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1 Introduction

Technological and economic development have taken place at a rapid pace in recent decades. Nowadays people are becoming more and more aware that this has not been without consequences. More than ever, the correlation between (over)consumption and environmental degradation has become clear (National-Academy-of-Sciences, 2020; Strand, Kovacic, Funtowicz, Benini, & Jesus, 2021; Trudel, 2019). The harmful consuming behavior ranges from depletion of the common pool resources (CPR), e.g. fishery, deforestation, mineral extraction and fossil fuel extraction (often referred to as "the tragedy of the commons") (World-Commission-on-Environment-and-Development, 1987), to overconsumption (and production) e.g. eating too much meat causing the livestock to be too large; flying too much; traveling unnecessarily much and inefficient via the road rather than carpooling or taking the train. All of this results in excessive air and soil pollution (Chermak & Krause, 2002).

It is indeed true that natural causes are also underlying climate change. Volcanic activity and anomaly in Earth's orbit around the sun, for example. Yet it seems that these causes are negligible as scientists fail to explain global warming by these factors (National-Academy-of-Sciences, 2020). Moreover, data shows that in the period from 1951 to 2010 the Earth's surface changed between -0.1 and 0.1 °C due to natural causes, and perhaps these natural effects balance themselves over a longer period of time. This cannot be said for anthropogenic causes of climate change that in the same period (1951-2010) caused the earth's surface to warm between 0.5 and 1.3 °C (Fahey, Doherty, Hibbard, Romanou, & Taylor, 2017). While this may seem like a small increase in global temperature, it is important to realize that this has happened in just a span of 60 years and that global warming had already started before this period. Without drastic changes the global temperature will keep rising exponentially and just with a few degrees the consequences can already be disastrous (National-Academy-of-Sciences, 2020). These consequences are noticeable in the present time. Examples are rising sea levels with an increased risk of flooding, disturbed ecosystems on land and in the sea, increased risk of extreme weather and natural disasters and increased risk of global pandemics.

It is clear that an increase in sustainable development and behavior is urgently needed. Finding how to stimulate this effectively is at the heart of this research. This paper so far will not leave it to the imagination that it is about environmental sustainability. Hence, a plain definition for sustainable development and behavior is indispensable. The World-Commission-on-Environment-and-Development (1987) defines sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs". This definition is widely used in studies related to this topic (e.g. Mota, Gomes, Carvalho, & Barbosa-Povoa, 2015; Scoones, 2007; A. Wilkinson, Hill, & Gollan, 2001) and has also been found to be appropriate in the context of this study. All this, the road to a solution in the fight against climate change, stands or falls with a change in (consumer's) behavior (Trudel, 2019).

Governments have not been shy about using public money to encourage activities that help mitigate negative externalities. Consider subsidizing farmers not to produce in areas where the environment is hypersensitive to pollution (Parry, 1998). Taxpayers' billions have been spent with such policies. While governments today still regularly use these neoclassical methods of subsidizing (and taxing) to manage externalities, alternative methods have been developed in recent years. Over time, economists increasingly agree that humans are not rational beings; agents have to deal with cognitive limitations. “Their behavior is influenced by desires and needs, social norms and values, infrastructural and institution context, and economic and political climate” (Lehner, Mont, & Heiskanen, 2016). From this discovery the synthesis of psychology, sociology and economics followed; behavioral economics was born (Colander, Holt, & Barkley, 2004).

By including cognitive limitations in economic analyses, awareness arose that (economic) behavior can be influenced. Policymakers saw how this could work to their advantage. As a result, the policy toolbox has been supplemented with the emergence of behavioral economics (Byerly et al., 2018; Troussard & Van Bavel, 2018; Uehara & Sakurai, 2021). One major advantage of such a policy is the cost aspect (Troussard & Van Bavel, 2018). One could question oneself why governments would use billions of public money to incentivize behavior when the same goals can be achieved by much cheaper behavioral influencing (Sunstein, 2015b; Thaler & Sunstein, 2003).

Since the discovery of the power of behavioral economics, the field has grown considerably in terms of (policy) instruments to use. *Nudging* dates back to a time when it did not even have a name. Think, for example, of all kinds of contracts with an annoyingly long list of terms and conditions that people signed blindly after which they were unintentionally tied to something (Thaler, 2018). This is nudging in the negative sense of the word, which Thaler (2018) calls "sludging". Policymakers saw the positive counterpart of sludging and since then they use it to change behavior on behalf of personal and societal benefits.

Thaler (2018), also known as the father of behavioral economics, defines nudging as "features that influence the decisions people make without changing either objective payoffs or incentives". Nudging is based on what is called *behavioral insights*. It are the insights on the human brain that lead to the cognitive limitations and biases, discovered through empirical studies. The most popular ones are often displayed with the mnemonic "MINDSPACE". Successively, the letters stand for: messenger, incentives, norms, default, salient, priming, affecting, commitment and emotion[1]. Sunstein (2015a) found that these behavioral insights can have major implications to promote sustainable behavior, even more than financial incentives.

Nudges can be divided into two major categories. (1) Policymakers can focus on prosocial behavior and social norms[2] (e.g. Bicchieri & Dimant, 2019; Kraft-Todd, Yoeli, Bhanot, & Rand, 2015) and (2) Policymakers can focus on individuals´ cognitive limitations, like with choice architecture[3] (e.g. Madrian, 2014; N. Wilkinson & Klaes, 2012). Despite this dichotomy, all instruments within these two larger categories have in common that they rely on cognitive limitations and emotions to establish desired behavior for oneself's or for society's sake (Byerly et al., 2018; Troussard & Van Bavel, 2018; Uehara & Sakurai, 2021).

Today much is known already about the power and effectiveness of nudging. Yet, different groups of people are subject to different life contexts and hence they may respond differently to (nudging) policies (Granovetter, 2005). In this study "groups" refers to two generational groups, generation X and Y. Later in this paper it will be explained what separates these generations and

[1] This paper is not purposed to elaborate on the detailed definition of nudging. Please refer to the original paper by Dolan et al. (2012) for further explanation of the MINDSPACE terms.

[2] Nudges that focus on prosocial behavior and social norms are nudges where certain behavior is established by forcing altruism and (fear for) reciprocity. This type of nudges are typically used for promoting public good contributions, among which environmental issues can be counted.

[3] Nudges that focus on individuals´ cognitive limitations are nudges where choice options are framed in such a way that the likelihood of choosing the desired option is increased. This type of nudges offer a solution in political context to help individuals make a decision when they themselves have difficulties with making the right decision or when people go for simplicity and refrain from deciding at all (Kahneman, Knetsch, & Thaler, 1991; Uehara & Sakurai, 2021). A famous example is automatically pension saving that helps present-biased people to provide themselves with financial resources in the future. Besides, this type of nudges is also widely used for public benefits such as being automatically opt-in for organ donation unless you actively take action to opt-out (Madrian, 2014).

why this may be relevant in the context of climate change and sustainable behavior. First it is important to be aware that to date little is known about the differences in effectiveness of nudges between generations, subject to widely deviating life contexts. This study therefore aims to discover through an online experiment, consisting of a survey, not only the difference in effects across two different nudge treatments, but also the differences in effects for two generational groups within those treatments. 265 respondents were collected, mainly via social media. Various private accounts as well as a business account with a varied type of customer were used for this purpose. What is found with the experiment is that with the behavioral nudges tested, there is on average no effect on peoples' sustainable behavior. However, there are positive effects for generation Y and negative effects for generation X if the amounts donated are followed. Yet, secondary analysis shows that the generational differences are rather small in terms of the probability that one donates after being nudged. Hence the results are not unambiguous. What should be noted is that the observed effects turn out to be statistically insignificant and the target group is rather small and limited in independence. Hence future research is recommended since the potential outcomes may be useful and relevant nowadays. After all, had significant effects how best to reach the different generational groups been found, this could have helped policymakers write more effective and efficient policies in the fight against what has become humanity's biggest challenge: climate change.

In the next section, section 2, several studies on nudging towards sustainable behavior are discussed and how insights collected from this may help to reduce climate change. It also provides the gap in the literature that will be addressed in this study. Section 3 gives an overview of this study´s research method, being an online experiment, and what specific nudges will be tested with it. Section 4 contains the results. First on the effectiveness of the nudges in general, considering aggregated data. Thereafter the differences in effectiveness of the nudges across generations. These results will be discussed in section 5, together with the strengths and limitations of this study. The conclusions that follow will be drawn in section 6.

2 Theoretical framework

It is "the greenhouse effect" that regulates the temperature on earth and thus makes life on earth possible. However, the effect has turned against humanity at the start of the industrial revolution when the emission of greenhouse gases (e.g. Carbon Dioxide, Methane and Nitrous Oxide) accelerated (National-Academy-of-Sciences, 2020). It has resulted in an enhanced greenhouse effect, leading to global warming and climate change with all its consequences of which some have mentioned in the introduction already.[4] Now is the time to curb this effect. In the remainder of this chapter several relevant studies on sustainability nudging are discussed, from which an underexposed aspect in science follows which is intended to be highlighted in this study. The generational groups are specified subsequently, followed by a research question to answer.

2.1 Nudging towards sustainable behavior – what literature suggests

Intra-generational climate control

Many studies have been done on nudging to make people behave more sustainably (e.g. Park & Barker, 2020; Reczek, Trudel, & White, 2018; Trudel, 2019). As mentioned above, consuming a lot of meat requires a large livestock which in turn has consequences for the environment. Park and Barker (2020) investigated how they can nudge people towards a more sustainable diet. They use choice architecture. By means of alternative framing of vegetarian dishes, i.e. by putting less emphasis on a dish that it is vegetarian and presenting it more as a "normal" dish on the menu, they show that people are more likely to choose a vegetarian dish. Comparably, Reczek et al. (2018) use alternative framing as well and find that sustainable consumer behavior is promoted by making consumers aware of the future consequences of unsustainable behavior. This notion is supported by Trope and Liberman (2003) who argue that making the future (consequences) salient makes people aware, resulting in more sustainable behavior. Moreover, Cialdini, Martin, and Goldstein (2015) show that emphasizing personal relevance of sustainable behavior for current generations improves behavior. The same goes for touching upon one's personal

[4] Because this exact greenhouse effect and its consequences can be interesting but fall outside the scope of this study, a more detailed explanation is included in Appendix A.

experiences with the consequences of climate change (Van der Linden, Maibach, & Leiserowitz, 2015; White, MacDonnell, & Dahl, 2011).

Next to these nudges that mainly focus on the subconscious of people, there are nudges that press social-emotional buttons. Human beings in nature care about status. Not only status to the outside world, but also to themselves; people care about their self-identity (Bodner & Prelec, 2003; Trudel, 2019) [5]. The cognitive mechanism behind this seems to be the avoidance of feelings of guilt (Higgins, 1987). This implies that people actually care intrinsically about climate change rather than just being extrinsically motivated by the outside world, which can be a helpful insight when constructing nudging policy.

Yet this outside world is also an important motivation for people to behave sustainably. Research shows that social norms are powerful in influencing human behavior (Bicchieri & Dimant, 2019; Kraft-Todd et al., 2015). Although social norms are unwritten rules, people tend to behave according to them. Adherence occurs if people are sufficiently convinced that others do the same (Bicchieri & Dimant, 2019). Social norms can therefore be induced by policy and thus used as a nudge. Goldstein, Cialdini, and Griskevicius (2008) investigated the effect of this form of nudging. In the experiment they conduct, the control and treatment group are differentiated by the message they receive. The treatment group received "Join your fellow guests in helping save the environment" while the control group received a standard, abstract message: "Help save the environment". The paper shows that hotel guests were more likely to reuse their towel when they were presented a message inducing a social norm, rather than an abstract message.

Inter-generational climate control

Since climate change as a problem spreads over several generations, a wide range of literature can also be found on sustainable behavior between generations and how this behavior can possibly be influenced by means of nudges, i.e. how current generations can be nudged to save the planet for future generations (Böhm, Gürerk, & Lauer, 2020; Fischer, Irlenbusch, & Sadrieh, 2004). Fischer et al. (2004) focus on prosocial behavior and social norms and show empirically

[5] Research shows that when people are made aware of their discrepancy between intended, sustainable behavior and their actual behavior, this triggers people to again behave in accordance with the intended behavior. Even more rigorous, reminding someone of their intended behavior even before they deviate from it, increases the chance that the person will stick to their intended behavior (Higgins, 1987). On top of this, Gao, Wheeler, and Shiv (2009) argue that once people have emotionally failed to fulfil their sustainable self-identity, they tend to compensate for this both cognitively and physically in order to keep the self-identity intact. Cognitive by eliminating unsustainable behavior against sustainable behavior, physically by purchasing environmentally friendly products after purchasing an environmentally unfriendly product.

that even when consequences for future generations are emphasized, current generations are prepared to stop the depletion of the common pool resources, but not sufficiently.

Böhm et al. (2020) dive into the more intrinsically based nudges. They explore nudges based on choice architecture, an instrument discussed earlier. However, Böhm et al. (2020) incorporate both an intra- and inter-generational prisoner's dilemma. They assume that behaving sustainably comes with costs and propose the following intra-generational prisoner's dilemma: why would one bear costs of behaving sustainably if others do not. Also, they assume that sustainability measurements for the long-term are more costly than the short-term ones, which brings an inter-generational dilemma: making high costs to protect the planet for future generations or lower costs to adapt to climate change for the benefits of current generations. Initially, it turns out that people tend to go for the cheaper option for the benefits of their own generation at the expense of future generations. However, Böhm et al. (2020) seek to explore how nudging can affect this "prisoner's" behavior. What follows from their experiment is that changing the default (e.g. putting electric cars or cars with low carbon emissions on the first pages of a car rental site) and self-commitment (e.g. asking employees to behave environmentally consciously at least at work) have significant positive effects on sustainable behavior, even while it is more costly. This again shows promising implications of nudging to limit climate change.

2.2 Missing literature on generational sensitivity to nudging

It is clear that as of today many is known about nudging and its relation to (inter-generational) sustainable behavior. When reading a paper on sustainability there is no denial on the urgence for behavioral change. Nevertheless, this behavior is insufficiently achieved in practice, despite frantic efforts through policy. Following Granovetter (2005), different groups of people (e.g. different generations) behave differently because of divergent social structures. In other words, different generations are subject to different contexts of life and have therefore different interests. This may imply that sensitivity to nudges varies across generational groups.

Little literature is available on the differences in effectiveness of certain nudges across generations. Hence no answer has yet been found on the question: *"What is the difference in effectiveness of behavioral nudges towards sustainable behavior between the pre-millennial and* *millennial generation?"*[6] An answer to this research question can give useful insights for policymaking. If it turns out that different generations respond differently to identical nudges, this could give policymakers hints that differentiation in nudges can increase its effectiveness. Concrete, nudges can then be adapted to the specific target group that it aims to influence. On the other hand, when it turns out that there are no generational differences, this also provides policymakers with useful information: they do not have to make an effort to differentiate between generations with nudging policies. An experiment using two different nudges will be carried out in this study to obtain this insight. The nudges to apply will be discussed in section 3.

2.3 The generational groups

This study aims to investigate generational differences in sensitivity to nudges. Generation X and Y have been taken as the target group. Although determining the year of birth that distinguishes one generation from another is not an exact science, generations are categorized for (scientific) analytical reasons (Dimock, 2018). Categorization is mainly based on major historical and social events that have impacted people in a different phase of life differently. In other words, people in the same generation have faced the same social, economic, political, technological and cultural events when they were a young adult (Ivanova, Flores-Zamora, Khelladi, & Ivanaj, 2018; Pew-Research-Center, 2015).

A study by Ivanova et al. (2018) that explores responsible consumer behavior across generational cohort X and Y finds that the latter shows more environmental friendly behavior than their predecessors. The probable reason argued is that generation Y grew up in an era where environmental issues became more salient. Additionally, in the 80s The World Commission on Environment and Development has been established following a series of environmental and human disasters, recognizing the problem for the first time worldwide (World-Commission-on-Environment-and-Development, 1987). Looking at the generational boundaries in Table 1 as they are often indicated by the literature (e.g. Ivanova et al., 2018; Williams & Page, 2011), the timing of these major political and environmental events justify the distinction between generation X's

[6] The motivation for the generational groups will be elaborated in section 2.3.

and generation Y’s sensitivity for behavioral nudges and their tendency towards sustainable behavior.

TABLE 1. GENERATIONS CHRONOLOGICALLY CATEGORIZED ON BIRTH YEAR BOUNDARIES.

Generation	***Period***
The silent generation	born 1928 to 1945
The baby boom generation	born 1946 to 1959
Generation X (Pre-Millennial generation)	**born 1960s to 1980s**
Generation Y (Millennial generation)	**born 1980s to 2000s**
Generation Z	born after 2000

Notes: Generational, chronological categorization based on years of birth. The table is based on categorization according to (Ivanova et al., 2018; Williams & Page, 2011), which states that social, economic, political, technological and cultural events lead the separation of generations.

For practical reasons, which are elaborated later in the Discussion section, the generational groups considered in this study are extended by seven years. The generations are then categorized as follows:

- **Generation X** (Pre-Millennial generation): 1952 up to and including 1979
- **Generation Y** (Millennial generation): 1980 up to and including 2007

2.4 Potential effects of nudging on sustainable behavior

Given the years they still have to go on this planet, younger generations will be more affected by climate change. Making concrete and felt that they have already (unconsciously) faced the consequences in the present and that they will more often in the future if no changes are made, may be a strong trigger for them to want to contribute to the necessary changes. Additionally, based on the theory that people naturally act out of self-interest when it comes to contributing to the public good, including climate control measures, the assumption could be made that older people are less willing to contribute because they will feel the effects of climate change less. This is supported by the experiment Böhm et al. (2020) conducted as has been discussed in section 2.1.

Diving deeper into the generational groups a profound counterarguments can be made. As discussed above has generation Y grown up in a more environmentally conscious world (Ivanova et al., 2018). The problems of climate change became more salient worldwide in the years of generation Y when there happened a series of natural and human disasters (Berkup, 2014; World-Commission-on-Environment-and-Development, 1987). Worldwide awareness is supported by the development of mass media channels on the internet that rapidly spread information globally (Berkup, 2014). This may have resulted in generation Y being raised more environmentally conscious, partly due to the increasing political focus on the environment over time. The lower standard of sustainable behavior for the older generation, generation X, simply because it was not salient during their upbringing, means that there is more room to improve on their behavior by nudging compared to the younger generation. Based on this, the hypothesis to be tested is: pre-Millennials are more sensitive to nudges towards sustainable behavior than Millennials.

3 The online experiment

This section will first discuss the nudges that have been selected for this study's experiment. Subsequently, it will be explained how the data was collected. To this end, the experimental design will be discussed, together with the substantiation for the choices made. Lastly, the method of statistical analysis will be discussed. Since the research subjects speak Dutch, the experiment was conducted in Dutch. Yet, its English translation will be displayed in this section. The original texts can be found in Appendix B.

3.1 Selecting the relevant nudges

In previous section various nudges have been reviewed. In this subchapter, the nudges that will serve this research will be selected on the basis of this.[7]

As shown above, several examples of choice architecture using alternative framing have proved successful (e.g. Böhm et al., 2020; Goldstein et al., 2008; Park & Barker, 2020; Reczek et al., 2018; Trope & Liberman, 2003). Small adjustment in formulation can yield great effects on behavior (Cialdini et al., 2015). Specifically, studies frequently advise that policies aiming for sustainable behavior should emphasize relevance for the current generation. This is what Trope and Liberman

[7] As this is a master thesis there are time and financial constraints that have to be dealt with. Given this the nudges chosen for this study's experiment will concern nudges that can be conducted in an online experiment with a one-off measurement.

(2003) refer to as “construal level theory” (CLT). The reasoning behind is that people naturally are present biased and therefore not sufficiently aware of the future consequences that they or their future generation, depending on one's life years ahead, will face. Put it differently, people tend to enjoy life now rather than invest in the environment for future benefits since the future feels too distant (Gillingham & Palmer, 2020).

Besides, making the relevance personal by triggering personal experiences contributes to behavioral changes as well (e.g. Van der Linden et al., 2015; White et al., 2011; Zaval, Markowitz, & Weber, 2015). Individuals take too little action because they underestimate their own personal impact on climate change as well as the consequences they will encounter personally - people see the problem as far removed from their own personal lives (Spence, Poortinga, & Pidgeon, 2012; Weber, 2006). Policy should therefore target on personal experiences to engage more people with sustainable behavior. This will make the problem more salient and felt (Li, Johnson, & Zaval, 2011).

Concrete, the nudges used in this study’s experiment will focus on (1) emphasizing that the “future” consequences of climate change are not as distant as they are perceived by many people and (2) making the actual consequences tangible by touching people's imagination via their personal experiences with climate change.

3.2 Experimental design

The experimental design consists of an online survey in which participants are exposed to one of three conditions: either a control condition, a *current problem treatment* or a *personal experience treatment*. These conditions serve as the independent variables in this study and determine the value for the dependent variable “tendency towards sustainable behavior”, measured by the amount of money a participant dedicates to an environmental charity after being exposed to one of the conditions.

Participants in the *control group* were displayed an abstract text related to climate change: "You have probably heard that the earth is overloaded, for example by deforestation and air pollution. This warms the earth and changes the climate." Afterwards, they were asked to indicate an amount between €0 and €100 they would be willing to donate to an environmental charity. This abstract text is the control condition and serves as the benchmark for the two treatment conditions. This benchmark is based on research showing that sustainable behavior often fails to materialize because incentives for sustainable behavior are formulated psychologically distant and abstract (Goldstein et al., 2008; McDonald, Chai, & Newell, 2015; Spence et al., 2012).

Participants in the *current problem treatment* were displayed a graph and text indicating that climate change is not a future problem, but one that humanity has been struggling with for years: "As can be seen in Figure 1, the average temperature in the Netherlands has risen sharply in recent decades (from 1990 onwards). Such an increase can also be seen in the average temperature on Earth. It shows that climate change is not a problem of the future, but a problem that has been going on in the world for years. This is because the earth is overloaded, for example by deforestation and air pollution." This was again followed by the request to indicate an amount between €0 and €100 that one would be willing to donate to an environmental charity. This treatment is inspired by literature that claims that people are present biased and see climate change as a future problem (Reczek et al., 2018; Trope & Liberman, 2003).

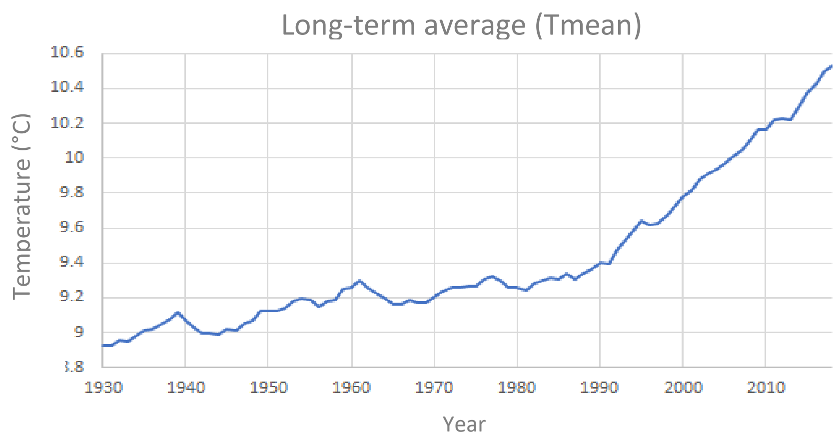

FIGURE 1. AVERAGE ANNUAL TEMPERATURE IN THE NETHERLANDS SINCE 1930. NOTE: THE GRAPH SHOWS THE AVERAGE TEMPERATURE IN THE NETHERLANDS OVER THE COURSE OF THE YEARS SINCE 1930, MEASURED IN °C. THE GRAPH IS ADAPTED TAKEN FROM "GEMIDDELDE TEMPERATUUR IN NEDERLAND: KANSBEREKENING," BY KEVIN (2019), WEERWOORD, (HTTPS://WWW.WEERWOORD.BE/M/2505902).

Participants in the *personal experience treatment* were displayed a text that emphasizes their personal experiences with the consequences of climate change: "Try to reflect on your life of the past 2 years. The years of global pandemic COVID-19 and all the misery and limitations it has brought into your life. If you thought you were just unlucky to have COVID-19 in your life, this will disappoint you. The chance that such world and life-changing events will occur again is increasing. This is because the earth is overloaded, for example by deforestation and air pollution." Once again this is followed by the question to indicate an amount that one would be willing to donate to an environmental charity. This treatment is inspired by literature that claims that people underestimate the extent to which climate change affects their own lives (Li et al., 2011; Spence et al., 2012; Weber, 2006).

3.3 Foundations for the experimental design

This study aims to determine the differences in sensitivity to nudges between generations. The target groups concern the previously defined generations X (born between 1952 and 1979) and Y (born between 1980 and 2007). Survey software Qualtrics' randomization tool has been used in order to have the same number of participants for each experimental condition as well as to have an equal distribution of participants across the conditions within both generational groups (i.e. block randomization). The randomization tool also takes care of the randomly assignment of participants to one of the conditions, which minimizes selection bias (Hernán, Hernández-Díaz, & Robins, 2004). All participants are exposed to the same survey except for the assigned condition. This yields highest possibility to draw justified conclusions on causality.

By having participants make a (fictitious) donation to an environmental charity after exposure to one of the experimental conditions, the effectiveness of the nudge is quantified. This makes it possible to draw conclusions about the differences in effectiveness of the nudges. Initially this is done for an across treatment comparison on aggregated data to get a first indication of which condition appears to be the most effective across the entire dataset. By then splitting the data in groups on the basis of generation, it is for each of the conditions analyzed which is most effective between the generations.

For the practical applicability of this study's results, e.g. for policymaking, observing actual sustainable behavior would be more accurate than the tendency towards sustainable behavior as measured in this study. The method used in this study is sensitive to hypothetical bias; the phenomenon where people donate an amount that they might not do in real life, resulting from the discrepancy between stated preferences and revealed preferences (de Corte, Cairns, & Grieve, 2021; N. Wilkinson & Klaes, 2012). This issue may apply in the context of this research, given that most people know that climate change is a major problem today and what normative behavior would look like, but nevertheless do not change their current behavior (Boström, 2020).

Despite its limitations the experiment in which a one-off measurement takes place was chosen in this study for time constraint reasons. Yet, to minimize hypothetical bias, a “cheap talk script" is incorporated prior to the experiment. This is nothing more than reducing the information asymmetry between parties which in this case are the researcher and the participants. Concrete, this means that there will be provided ex-ante information for the participant on the existence of hypothetical bias and that one therefore should try the best to imagine oneself to really donate the amount of money as devoted in the experiment (Wuepper, Clemm, & Wree, 2019). This cheap talk script turns out to be credible as it increases realism of the data, while it has no direct influence on one’s behavior or choice shown in the real world setting. Thus, the cheap talk script will not hamper causality measurement as it would not serve as an additional nudging aspect (Chakraborty & Harbaugh, 2007). Moreover, all three conditions involve the same one-off measurement and may therefore be subject to hypothetical bias in similar ways. Given this, with this experimental design it is still considered possible to investigate which nudge is most effective in general and per generational group, in order to provide policymakers with insight into this.

3.4 Participants and statistical analysis

265 anonymous participants born between 1952 and 2007 took part in the experiment concerning an online survey. All observations were collected in the period from April 20th to May 2th, 2022. Participants have been selected through various channels, of which social media is the main part. Participants are incentivized with a raffle of two vouchers for Bol.com worth €25. In addition to distribution via various private social media accounts, an external company was called upon to distribute the experiment. The latter is a fire protection company that has a varied customer base given their industry. Distributing through both private accounts of various people and a broadly oriented corporate account limits selection bias. None of the participants was informed that they have been randomly assigned to either the control group, the *current problem treatment* or the *personal experience treatment* to hold them as objective as possible.

The experimental design is constructed in a way that the dependent variable is expressed by an amount of money between €0 and €100, hence participants in the experiment are limited in contributing to climate change prevention by a maximum amount of €100. However, one might be willing to contribute even more than €100. Since the experimental design does not allow this, the assigned value would not truly reflect the real value and a non-linear model can appear. A tobit regression model distinguishes itself from an Ordinary Least Squares (OLS) model by taking these limitations into account (UCLA, 2021). Still, an OLS regression model will be used as the best unbiased estimator. This is possible according to Modern Gauss-Markov Theorem, which distinguishes itself from the Classical Gauss-Markov Theorem by abandoning the linearity assumption given its unnecessity (Hansen, 2021). Nevertheless, a tobit regression model will be used as a robustness check. Furthermore, there may potentially be large variation in willingness to contribute to the prevention of climate change (i.e. donation varies widely). A structure is hard to predict here. Therefore robust standard errors for the OLS model are appropriate (Mansournia, Nazemipour, Naimi, Collins, & Campbell, 2020).

Moreover, this study aims to measure causality between nudges and tendency towards sustainable behavior. Attention to possible alternative explanations for the observed effects is therefore important. To this end, the control variables exact age, gender, income, whether someone has children and whether someone has previously donated to a charity are included in both the OLS and tobit regression models. These variables serve to rule out that there is no other driver for the observed results than the actual treatments, which may happen, for instance, if, despite the randomization process, participants with similar socio-demographic characteristics are clustered. Non-parametric ranksum tests will be conducted to test for this clustering. In Appendix C the choice for these specific control variables is elaborated.

Up to this point the analysis with donation as the dependent variable has been discussed. Still, this analysis may be biased. If relatively few people donate within a certain condition, but these people also all make a relatively high donation, it can make a condition look effective. Though, this positive image may be distorted. For example when many participants under a different condition donate, but all donate a relatively low amount. It is therefore valuable to also look at the extensive margin, i.e. the probability of donating at all. A new analysis will be performed for this purpose. A linear probability model will be run with the dummy variable "donating" as dependent variable. This variable is assigned a value of 1 for each participant who donates >€0 and otherwise a value of 0. The coefficients then indicate the probability that a participant that is exposed to a certain condition makes a donation higher than €0.

4 Experimental results

The presentation of the results will follow the structure as indicated in previous section. First the across treatment comparison will be shown to get an initial indication of the effects the nudges have and which one turns out to be most effective among the entire dataset. For this purpose both treatments are compared to the control sample of the aggregated data. Subsequently, the analysis on generational differences within the conditions will be presented. Here the treatment conditions per generational group are compared to the control sample of their own respective generation. Since two different dependent variables have been analyzed there are two general statistics to summarize here. Table 2 provides summary statistics separated by sample size, mean donation and standard deviation per experimental sample.

Table 3 provides summary statistics separated by whether one donates at all per experimental sample.

TABLE 2. SUMMARY STATISTICS (MEAN, SD AND N) BY EXPERIMENTAL CONDITION

AGGREGATED DATA	**Mean**	**SD**	**N**
Control group	26.47	25.50	87
Current problem treatment group	24.96	23.34	89
Personal experience treatment group	26.96	23.11	89
GENERATIONAL DATA	**Mean**	**SD**	**N**
Control group generation X	37.00	30.65	40
Control group generation Y	17.51	15.51	47
Current problem group generation X	27.64	27.09	42
Current problem group generation Y	22.55	19.39	47
Personal experience group generation X	31.43	26.84	42
Personal experience group generation Y	22.96	18.57	47

Notes: Summary statistics divided into experimental conditions. The upper part of the table contains the summary statistics for the aggregated data (i.e. the across treatment comparison) and the lower part contains generational data (i.e. the within treatment, but across generations comparison). The table shows for each of the samples the number of participants (N) involved. Besides, the mean shows for each of the conditions what amount (€) has been donated on average. The standard deviation (SD) indicates how within each sample the distribution of the donations is around the mean.

TABLE 3. SUMMARY STATISTICS (DONATING OR NOT) BY EXPERIMENTAL CONDITION

AGGREGATED DATA	**N donating**	**N**	**% donating**
Control group	84	87	96.6%
Current problem treatment group	81	89	91.0%
Personal experience treatment group	81	89	91.0%
GENERATIONAL DATA	**N donating**	**N**	**% donating**
Control group generation X	40	40	100%
Control group generation Y	44	47	93.6%
Current problem group generation X	39	42	92.7%
Current problem group generation Y	42	47	89.4%
Personal experience group generation X	40	42	95.2%
Personal experience group generation Y	41	47	87.2%

Notes: Summary statistics divided into experimental conditions. The upper part of the table contains the summary statistics for the aggregated data (i.e. the across treatment comparison) and the lower part contains generational data (i.e. the within treatment, but across generations comparison). The table shows for each of the samples the number of donating participants (N donating). Besides, it shows the total amount of observations per sample (N), followed by the percentage of donating participants per sample.

4.1 Comparing donated amounts across treatments

The across treatment comparison was made on the basis of both a linear OLS regression model with robust standard errors and a tobit regression model. Various influences, like socio-demographic variables, may or may not induce people to donate more. Age, gender, whether someone has children or not, whether someone donated before to environmental charity and income are included in model 3 and 4 as control variables to account for this. The results are presented in Table 4. The tests for the OLS assumptions are included in Appendix D. Both models with control variables included are statistically significant; model 3 (p = 0.0022) and model 4 (p = 0.0017). Treatment 1, the *current problem treatment*, appears to have a negative effect in contrast to the control condition. Treatment 2, the *personal experience treatment*, shows varying effects; a (slight) positive effect in the OLS regression and a negative effect in the tobit regression. This can be summarized as Result 1 below. Though, none of these relevant treatment variables show statistically significance. According to power analysis the sample size should be 34,918 for significance (power = 80% α = 0.05) based on these results.[8]

Robustness tests have been conducted. For the *current problem treatment* the results from the regressions that there is no statistically significant effect compared to the control group has been

[8] Since sample sizes need to be larger for significant results when the mean difference is small, the power calculation is based on the smallest mean difference: personal experience treatment in contrast to the control group (Δ = 0.49).

confirmed (two sided ranksum test: N=176, *p*=0.81), likewise as for the *personal experience treatment* (two sided ranksum test: N=176, *p*=0.40). Moreover, a robustness test shows that there is no statistically significant difference in effects between both treatments (two sided ranksum test: N=178, *p*=0.32).

Result 1: The current problem treatment has a negative effect on the amount people donate. The personal experience treatment shows ambiguous effects.

TABLE 4. ORDINARY LEAST SQUARES (OLS) AND TOBIT REGRESSIONS TO PREDICT TREATMENT EFFECTS

Dependent variable: Donation	Excl. control variables		Incl. control variables	
Model:	Model 1 OLS	Model 2 Tobit	Model 3 OLS	Model 4 Tobit
Control group	26.47*** (0.000)	26.54*** (0.000)	16.35* (0.027)	16.06* (0.036)
Current problem treatment	-1.516 (0.681)	-2.618 (0.515)	-1.296 (0.715)	-2.273 (0.561)
Personal experience treatment	0.484 (0.895)	-0.665 (0.869)	0.0674 (0.985)	-1.171 (0.764)
Age			0.351** (0.003)	0.689*** (0.001)
Gender dummy			0.586 (0.856)	-0.793 (0.813)
Having children dummy			-2.834 (0.415)	-3.035 (0.403)
Having donated before to charity dummy			7.727** (0.010)	8.972* (0.013)
Income			-0.194 (0.795)	-0.267 (0.693)
Number of observations	265	265	257	257
F-value	0.18		3.31	
Chi²		0.46		23.06
R^2	0.001		0.084	
Pseudo R^2		0.0002		0.01

Notes: Model 1 is the OLS regression model with robust standard errors. Model 2 is a tobit regression model since data for donation as the dependent variable is censored (respondents can donate no more than €100) (UCLA, 2021). Model 3 and model 4 are again an OLS with robust standard errors and a tobit model respectively, but with control variables included. The control group coefficient is the benchmark where the current problem treatment and personal experience treatment are contrasted to. For the gender dummy, the coefficient denotes an additional effect when a participant is a male. For the other dummies the coefficients denote an additional effect if the variable is true for a participant.

p-values in parentheses: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Since age seems to drive the donated amount separate regressions have been run for all conditions to observe the effect of age itself in each of the conditions. The results are displayed in Table 5. What turns out is that for the aggregated samples there is for both the control and the current problem treatment a significant model (*p* = 0.003 and *p*=0.009 respectively). Besides, for these two conditions a significant positive relationship between age and donated amount exists. This can be summarized as Result 2 below. To check for model robustness a tobit regression has been run. The tobit regression yields similar results as the standard OLS.

TABLE 5. ORDINARY LEAST SQUARES (OLS) AND TOBIT REGRESSIONS TO PREDICT AGE EFFECTS BY TREATMENT

Dependent variable: Donation Independent variable: Age				
Model:	Model 1 OLS		Model 2 Tobit	
Control group	Constant	14.450*** (0.001)	Constant	13.017** (0.008)
	Age	0.482** (0.003)	Age	0.542** (0.002)
Current problem treatment	Constant	15.540*** (0.000)	Constant	13.461** (0.006)
	Age	0.401** (0.009)	Age	0.447** (0.008)
Personal experience treatment	Constant	23.638*** (0.000)	Constant	22.214*** (0.000)
	Age	0.143 (0.361)	Age	0.160 (0.353)

Notes: Models under model 1 are separate OLS regression with robust standard errors and models under model 2 are separate tobit regressions. The single regression models predict how the amount donated by participants in the conditions are explained by participants' age. The constant is the intercept denoting the average donation in the sample. The coefficient denotes the effect age has on the amount donated.

p-values in parentheses: * p<0.05, ** p<0.01, *** p<0.001

Result 2: For the control condition and the current problem treatment there is a positive relationship between age and the donated amount.

4.2 Comparing the probability of donating across treatments

Likewise as for the analysis above, two OLS regressions were performed; once including control variables and once excluding control variables. The results are presented in Table 66. The tests for the model assumptions are included in Appendix E. The control variables including LPM appears to be statistically significant (p=0.03). The results show that the control condition leads to a high probability of participants donating (100%). For both treatments the probability of donating is lower compared to the control group, denoted by the negative coefficients: 96.4% for the current problem treatment and 93.3% for the personal experience treatment. This can be summarized as Result 3 below. However, no statistical significance is reached for the coefficients of both treatments. According to power analysis the sample size should be 126 for significance (margin of error = 5% confidence interval = 95%). To test for robustness of the linear probability model probit models have been run as well. The marginal effects are shown in Table 5. Once again the version with control variables included, model 4, turns out to be statistically significant (p=0.0001). The results show roughly similar effects as the LPM does. However, the result regarding the personal experience treatment turns statistically significant.

TABLE 6. LINEAR PROBABILITY MODEL (LPM) TO PREDICT THE PROBABILITY OF DONATING AT ALL

Dependent variable: Donating or not (dummy)	Excl. control variables		Incl. control variables	
Model:	Model 1 LPM	Model 2 Probit	Model 3 LPM	Model 4 Probit
Control group	0.966***	1.819***	1.000***	2.371**
	(0.000)	(0.000)	(0.000)	(0.003)
Current problem treatment	-0.055	-0.064	-0.056	-0.063
	(0.128)	(0.139)	(0.121)	(0.118)
Personal experience treatment	-0.055	-0.064	-0.067	-0.084*
	(0.128)	(0.139)	(0.082)	(0.040)
Age			0.001	0.001
			(0.424)	(0.387)
Gender dummy			-0.107**	-0.102***
			(0.004)	(0.001)
Having children dummy			-0.009	-0.001
			(0.801)	(0.968)
Having donated before to charity dummy			0.063	0.061
			(0.125)	(0.060)
Income			-0.006	-0.006
			(0.451)	(0.491)
Number of observations	265	265	257	257
F-value	1.80		2.27	
Wald chi^2		2.73		31.2
R^2	0.010		0.075	
Pseudo R^2		0.022		0.152

Notes: Model 1 and 3 are binary probability regressions with robust standard errors. Model 2 and 4 are probit models with robust standard errors. In model 1 and 2 control variables are excluded whereas they are included in models 3 and 4. As the dependent variable has been taking a dummy denoting whether a participant donated or not. In LPM models 1 and 3 the control group coefficient denotes the probability that a participant in this group donates and serves as the benchmark where the current problem treatment and personal experience treatment are contrasted to. For the gender dummy, the coefficient denotes an additional effect when a participant is a male. For the other dummies the coefficients denote an additional effect if the variable is true for a participant. Notice that for the probability in percentages the coefficients have to be multiplied by 100. For probit model 2 and 4 the margins have been determined, hence the coefficients can also be interpreted as changes in probabilities.

p-values in parentheses: * p<0.05, ** p<0.01, *** p<0.001

When testing for robustness of the effects the models show, it yields exactly the same results for both treatment groups when comparing them with the control group. For both treatments it does not show that the probability of donating differs significantly compared to the probability of donating in the control condition (two sided ranksum test: N=176, p=0.13). When testing for both treatment groups it results that the probability of giving is equal for both treatments. However, the equality is not statistically significant (two sided ranksum test: N=178, p=1.000). These tests align with the non-significance shown by the regression results.

Result 3: The control condition shows a maximum probability of donating of 100%. The current problem and personal experience treatments both score lower, yet the probability is still rather high for both treatments.

4.3 Comparing donated amounts within treatments, but across generations

A second analysis was performed for the within treatment, but across generations comparison. This comparison is also based on both a linear OLS regression with robust standard errors and a tobit regression model. Again both with and without the same control variables as before except age since generation is subject to age. The results are presented in Table 77. The tests for the OLS assumptions are included in Appendix F. Both models excluding control variables, model 1 (p=0.0019) and model 2 (p=0.0012) as well as both models including control variables, model 3 (p=0.0017) and model 4 (p=0.0026), are significant. For starters, looking at the coefficients for the control groups for both generations, it is noticeable that in generation Y the coefficient is lower compared to generation X. This can be summarized as Result 4 below. Then, when the treatment effects of the generations are compared with their own respective control group, it is noticeable that for generation X both treatments have a negative effect, whereas the effects are positive on generation Y.[9] This can be summarized as result 5 below. Yet, comparing the generations within treatments, it follows that generation X still makes higher donations compared to generation Y. This can be summarized as Result 6 below. Though, only one of the relevant treatment variables shows statistically significance. Based on these results power analysis prescribes a sample size of

[9] Please, read the table notes carefully to make sensible interpretations of the coefficients.

TABLE 7. ORDINARY LEAST SQUARES (OLS) AND TOBIT REGRESSIONS TO PREDICT GENERATIONAL TREATMENT EFFECTS

Dependent variable: Donation	Excl. control variables		Incl. control variables	
Model:	Model 1 OLS	Model 2 Tobit	Model 3 OLS	Model 4 Tobit
Control group generation X	37.00*** (0.000)	38.26*** (0.000)	25.28* (0.017)	26.83* (0.013)
Control group generation Y	-19.49*** (0.000)	-21.73*** (0.000)	-10.64 (0.135)	-12.31 (0.082)
Current problem treatment gen X	-9.36 (0.145)	-11.01 (0.053)	-7.79 (0.228)	-9.35 (0.102)
Current problem treatment gen Y	14.40 (0.051)	15.51* (0.047)	12.02 (0.105)	13.13 (0.092)
Personal experience treatment gen X	-5.57 (0.382)	-7.05 (0.215)	-3.870 (0.545)	-5.253 (0.353)
Personal experience treatment gen Y	11.02 (0.131)	11.65 (0.135)	7.19 (0.334)	7.46 (0.335)
Age			0.280* (0.046)	0.294* (0.043)
Gender dummy			0.342 (0.916)	-1.042 (0.755)
Having children dummy			-4.210 (0.274)	-4.790 (0.232)
Having donated before to charity dummy			6.902* (0.030)	7.896* (0.036)
Income			-0.210 (0.784)	-0.292 (0.666)
Number of observations	265	265	257	257
F-value	3.91		2.94	
Chi²		20.05		26.99
R^2	0.07		0.097	
Pseudo R^2		0.009		0.012

Notes: Model 1 is the OLS regression with robust standard errors. Model 2 is a tobit regression since data for donation as the dependent variable is censored (respondents can donate no more than €100) (UCLA, 2021). Model 3 and model 4 are again an OLS with robust standard errors and a tobit model respectively, but with control variables included. Due to the use of dummies, where only one reference group is chosen, all coefficients have been compared against generation X's control group. For the coefficients of generation X, this does not provide any extraordinary interpretations. For generation Y, however, a calculation must be made for correct interpretation: (1) subtract the control group coefficient for generation Y from the control group coefficient of generation X. This gives the direct benchmark for generation Y. (2) Add up control coefficient generation X + control coefficient generation Y + current problem treatment coefficient gen X + current problem treatment coefficient gen Y = outcome for the treatment group of the current problem treatment for generation Y. (3) combine 1 and 2, meaning that you compare the treatment outcome of step 2 with the benchmark of step 1 to get the treatment effect. This works exactly the same for the personal experience treatment for generation Y, except that in step 2 the coefficients of the personal experience treatment should be taken instead of the current problem treatment coefficients. For the gender dummy, the coefficient denotes an additional effect when a participant is a male. For the other dummies the coefficients denote an additional effect if the variable is true for a participant.

p-values in parentheses: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

233 for significant results (power = 80% α = 0.05).[10]

Robustness tests have been conducted to check whether the treatment effects differ significantly from the effect in the control condition. For treatment 1, the *current problem treatment*, the results from the regressions that there is no statistically significant difference in effects between the generational samples have been confirmed (two sided ranksum test: N=89, p=0.59), likewise as for treatment 2, the *personal experience treatment* (two sides ranksum test: N=89, p=0.23). Robustness tests have also been conducted to compare the generational samples within the conditions. Within the control condition it turns out that the effect across generations differs significantly (two sided ranksum test: N=87, p=0.0002). Within both treatment conditions the effects do not differ statistically significant across generations (two sided ranksum tests: N=89, p=0.59 and N=89, p=0.23 respectively); once again a confirmation of the regression results.

Result 4: The amount one donates in the control group of generation Y is lower compared to one in the control group of generation X.

Result 5: Both nudges have a positive effect on generation Y, whereas the effect is negative on generation X when comparing the treatment coefficients to the generations' respective control coefficient.

Result 6: Despite negative effects of nudges on generation X when comparing the treatment coefficients to the respective control group, all conditions yield higher donations in generation X compared to generation Y when comparisons are made across generations but within treatments. Moreover, when comparing the nudges within generations it follows that for both generations the amount donated is highest in the personal experience treatment.

Looking at the results, in the generational analysis age seems to drive the donated amount whereas generation does not. Again separate regressions have been run for all conditions and generational samples separately to observe the effect of age itself. The results are displayed in Table 8. For the generational samples only for the current problem treatment in generation X there is a significant model (p=0.05) together with a significant positive relationship between age

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[10] Since sample sizes need to be larger for significant results when the mean difference is small, the power calculation is based on the smallest mean difference: control group generation Y – current problem treatment generation Y (Δ = 5.04).

and donated amount. This can be summarized as Result 7 below. To check for model robustness a tobit regression has been run. The tobit regression yields similar results as the standard OLS.

TABLE 8. ORDINARY LEAST SQUARES (OLS) AND TOBIT REGRESSIONS TO PREDICT AGE EFFECTS BY TREATMENT

Dependent variable: Donation Independent variable: Age				
Model:	Model 1 OLS		Model 2 Tobit	
Control group gen X	Constant	39.374 (0.197)	Constant	43.226 (0.155)
	Age	-0.127 (0.881)	Age	-0.190 (0.824)
Control group gen Y	Constant	14.103*** (0.000)	Constant	13.266*** (0.000)
	Age	0.263 (0.272	Age	0.286 (0.070)
Current problem treatment	Constant	-15.715 (0.420)	Constant	-26.610 (0.260)
gen X	Age	1.216* (0.048)	Age	1.506* (0.023)
Current problem treatment	Constant	17.008*** (0.000)	Constant	15.855*** (0.000)
gen Y	Age	0.438 (0.068)	Age	0.443* (0.041)
Personal experience treatment	Constant	14.484 (0.454)	Constant	14.032 (0.535)
gen X	Age	0.488 (0.417)	Age	0.495 (0.439)
Personal experience treatment	Constant	25.587*** (0.000)	Constant	24.743*** (0.00)
gen Y	Age	-0.203 (0.083)	Age	-0.243 (0.259)

Notes: Models under model 1 are separate OLS regression with robust standard errors and models under model 2 are separate tobit regressions. The single regression models predict how the amount donated by participants in the conditions are explained by participants' age.

p-values in parentheses: * p<0.05, ** p<0.01, *** p<0.001

Result 7: When data is grouped into generational samples and the relationship between age and the amount donated is analyzed, it appears that only in the generation X sample of the current problem treatment there is a positive relationship between age and the amount someone exposed to this treatment donates.

4.4 Comparing the probability of donating within treatments, but across generations

Also for the across generations comparison a linear probability model with "donating" as the dependent variable has been performed. It again concerns two linear probability models, one including and one excluding control variables. The results are presented in Table 99. The tests for the model assumptions are included in Appendix G. Of those two the model where control variables are excluded is statistically significant (p=0.0013). The probability of a participant to donate scores 100% in the control group for generation X. This probability has not been reached by generation Y's control group as shown by their negative coefficient. The probability in this group amounts 93.6%. This can be summarized as Result 8 below. Within the current problem

TABLE 9. LINEAR PROBABILITY MODEL (LPM) TO PREDICT THE PROBABILITY OF DONATING AT ALL

Dependent variable: Donating or not (dummy)	Excl. control variables		Incl. control variables	
Model:	Model 1 LPM	Model 2 Probit	Model 3 LPM	Model 4 Probit
Control group generation X	1.000*** (0.000)	Not estimable	1.070*** 0.000	Not estimable
Control group generation Y	-0.064 (0.078)	Not estimable	-0.055 (0.308)	Not estimable
Current problem treatment gen X	-0.071 (0.077)	Not estimable	-0.082* (0.048)	Not estimable
Current problem treatment gen Y	0.029 (0.683)	Not estimable	0.048 (0.501)	Not estimable
Personal experience treatment gen X	-0.048 (0.153)	Not estimable	-0.057 (0.122)	Not estimable
Personal experience treatment gen Y	-0.016 (0.816)	Not estimable	-0.020 (0.784)	Not estimable
Age			0.0002 (0.904)	0.0003 (0.858)
Gender dummy			-0.108** (0.004)	-0.122*** (0.001)
Having children dummy			-0.024 (0.601)	-0.021 (0.628)
Having donated before to charity dummy			0.055 (0.191)	0.068 (0.078)
Income			-0.006 (0.424)	-0.007 (0.448)
Number of observations	265		257	
F-value	4.11		1.86	
R^2	0.025		0.080	

Notes: Model 1 and 3 are binary probability regressions with robust standard errors and excluding and including control variables respectively. As the dependent variable has been taking a dummy denoting whether a participant donated or not. Due to the use of dummies, where only one reference group is chosen, all coefficients have been compared against the control group of generation X. For the coefficients of generation X, this does not provide any extraordinary interpretations. For generation Y, however, a calculation must be made for correct interpretation: (1) subtract the control group coefficient for generation Y from the control group coefficient for generation X. This gives the direct benchmark for generation Y. (2) Add up control coefficient generation X + control coefficient generation Y + current problem treatment coefficient gen X + current problem treatment coefficient gen Y = outcome for the treatment group of the current problem treatment for generation Y. (3) combine 1 and 2, meaning that you compare the treatment outcome of step 2 with the benchmark percentage of step 1 to get the treatment effect. This works exactly the same for the personal experience treatment for generation Y, except that in step 2 the coefficients of the personal experience treatment should be taken instead of the current problem treatment coefficients. For the gender dummy, the coefficient denotes an additional effect when a participant is a male. For the other dummies the coefficients denote an additional effect if the variable is true for a participant. Notice that for the probability in percentages the coefficients have to be multiplied by 100. Model 2 and 4 are probit models where model 2 shows no results. The results in model 4 can be interpreted similar as model 3.

p-values in parentheses: * p<0.05, ** p<0.01, *** p<0.001.

treatment there is a probability of 92.2% that one belonging to the generation X group donates, whereas for the generation Y group this probability is 89.4%. For the personal experience treatment the probabilities amount 95.2% and 87.2% for generation X and Y respectively. This can be summarized as Result 9 below. Yet again the coefficients are not statistically significant. Power analysis proposes a sample size of 172 for significance (margin error = 5% confidence interval = 95%). Moreover, guarantees for model robustness are low since STATA lists the relevant variables as not estimable. Only the coefficients for the control variables are estimated.

Robustness tests show that for none of the conditions the probability of a participant donating is significantly different when generation X and Y are compared (two sided ranksum test: N=87, p=0.11; N=89, p=0.57 and N=89, p=0.19 for control, current problem treatment and personal experience treatment respectively). With these results the tests confirm what is suggested by the regressions: no significant generational differences in effects are observed with the experiment.

Result 8: Comparing the control groups for both generations it follows that with a score of 100% for generation X the probability of donating is higher for this generation's control group compared to a probability of 93.6% for generation Y.

Result 9: For both treatments the probability of donating is higher in generation X's samples compared to generation Y's samples. Regarding the most effective nudge on probability of donating the results are mixed: for generation X the probability of donating is higher in the personal experience treatment whereas for generation Y the probability of is higher in the current problem treatment.

4.5 Test for socio-demographic clustering

To check for socio-demographic clustering within the samples non-parametric ranksum tests have been conducted. The results are displayed in Appendix H. For the across treatment comparison no significant differences on socio-demographic variables have been found across the samples, hence the randomization of participants over the experimental conditions proceeded properly here. For the across generations comparison the ranksum tests have shown that for all experimental conditions the control variables regarding whether one has children and whether someone donated before to a charity do differ significantly across the generational samples. Checking the data it follows that in generation X indeed way more participants have children compared to in generation Y. The same goes for whether someone donated before to a charity. These socio-demographics might be alternative explanations for the observed results, hence they will be discussed later in the Discussion section.

Furthermore, since age clustering between the generations is obvious given the sampling on the basis of generations, which is subject to age, for the between generations analysis only tests

TABLE 10. SUMMARY STATISTICS ON SOCIO-DEMOGRAPHICS BY TREATMENT

SAMPLE	**Age**	**Gender**	**Donated before**	**Having children**
AGGREGATED SAMPLES				
Control group	Mean: 37.6 SD: 16.0 Range: 20 – 69	Male: 32 Female: 53	Yes: 50 No: 34	Yes: 49 No: 35
Current problem treatment	Mean: 38.5 SD: 16.1 Range: 15 - 69	Male: 37 Female: 52	Yes: 59 No: 30	Yes: 47 No: 42
Personal experience treatment	Mean: 38.2 SD: 15.9 Range: 16 – 68	Male: 29 Female: 60	Yes: 61 No: 27	Yes: 47 No: 41
GENERATIONAL SAMPLES				
Control group generation X	Mean: 49.4 SD: 6.5 Range: 42 - 69	Male: 15 Female: 23	Yes: 32 No: 6	Yes: 35 No: 3
Control group generation Y	Mean: 27.9 SD: 15.0 Range: 20 - 38	Male: 17 Female: 30	Yes: 18 No: 28	Yes: 14 No: 32
Current problem treatment gen X	Mean: 50.6 SD: 7.3 Range: 42 - 69	Male: 15 Female: 27	Yes: 39 No: 3	Yes: 36 No: 6
Current problem treatment gen Y	Mean: 27.7 SD: 14.0 Range: 15 - 42	Male: 22 Female: 25	Yes: 20 No: 27	Yes: 11 No: 36
Personal experience treatment gen X	Mean: 49.7 SD: 7.1 Range: 42 - 68	Male: 14 Female: 28	Yes: 36 No: 6	Yes: 35 No: 7
Personal experience treatment gen Y	Mean: 28.0 SD: 14.4 Range: 16 - 39	Male: 15 Female: 32	Yes: 25 No: 21	Yes: 12 No: 34

Notes: The table summarizes the data on the socio-demographic variables, except income, by treatment. In order to keep the table clear, income is displayed separately.

on age clustering within the generations have been conducted and not between the generations. It resulted that when comparing the generational treatment samples with the control sample for their own respective generation, no sign of accidental age clustering appears. What however strikes is that looking at the age standard deviations for generational samples, the differences in participant's ages are much smaller within each generation X sample compared to generation Y samples. Moreover, considering the age boundary of 42 separating the generations, the sample means of generation Y are predominantly in the middle of their generational class (15 – 42), while generation X tends relatively much towards the lower age limit of the generation (42 – 69). All socio-demographics except income are summarized by treatment in Table 1010. Income is summarized in Figure 2. Income class distribution by treatment across aggregated samples. The Y-axes denotes the number of participants in the samples that fall within the income classes given on the X-axes.Figure 2 and Figure 3 for the aggregated samples and the generational samples respectively. The tables provide an indication on how generation X and Y differ.

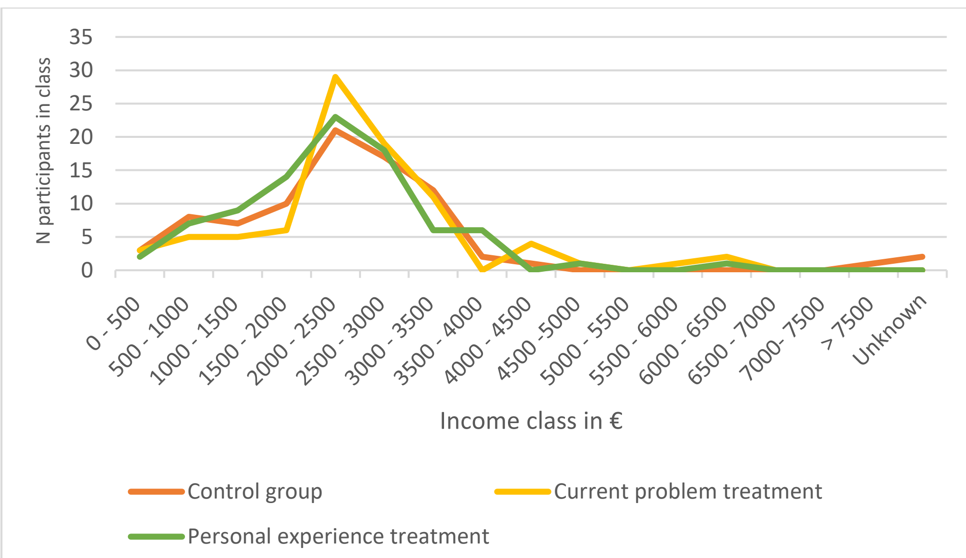

FIGURE 2. INCOME CLASS DISTRIBUTION BY TREATMENT ACROSS AGGREGATED SAMPLES. THE Y-AXES DENOTES THE NUMBER OF PARTICIPANTS IN THE SAMPLES THAT FALL WITHIN THE INCOME CLASSES GIVEN ON THE X-AXES.

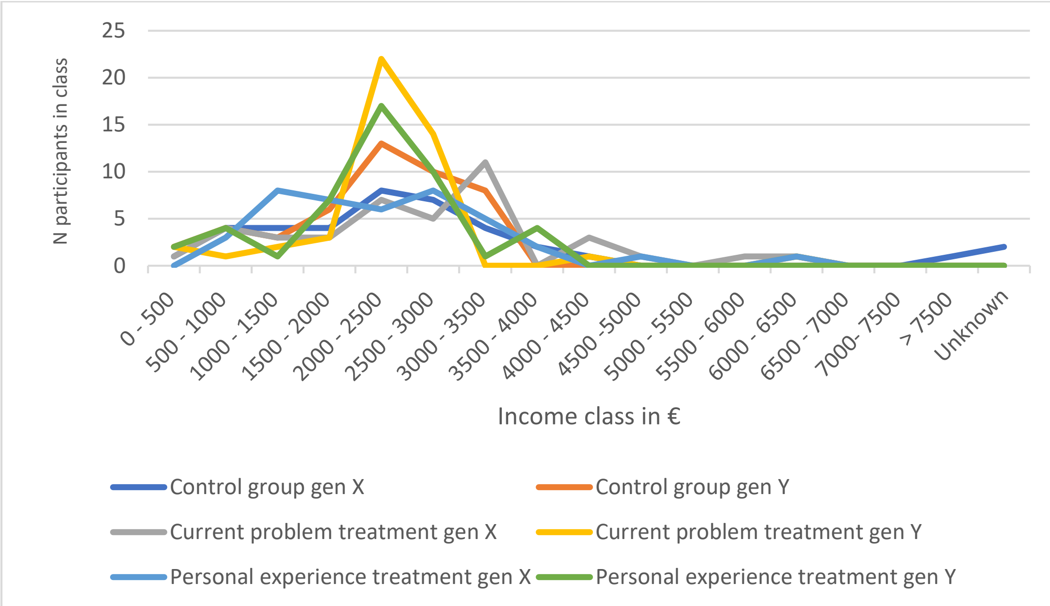

FIGURE 3. INCOME CLASS DISTRIBUTION BY TREATMENT ACROSS GENERATIONAL SAMPLES. THE Y-AXES DENOTES THE NUMBER OF PARTICIPANTS IN THE SAMPLES THAT FALL WITHIN THE INCOME CLASSES GIVEN ON THE X-AXES.

5 Discussion

5.1 Discussing the results

The results of the analyses related to the between-treatment comparison show that the nudges towards sustainable behavior have no effect on average, whereas they do have an effect on the different generations. The generational effect however is ambiguous, leaving the hypothesis to be tested in this study alive. I.e. even though millennials seem to be more sensitive to nudges towards sustainable behavior compared to pre-millennials, the ambiguous results are not sufficiently decisive to either accept or reject the hypothesis as will be elaborated below.

Starting off with the analysis where the donated amount is concerned it follows that where the younger generation, generation Y, turns out to be sensitive to nudges towards sustainable behavior, the nudges are counter effective for the older generation, generation X. Although this result seems unusual, especially the negative effect of nudges on the tendency to sustainable behavior in generation X, this could be caused by the high score for the control group of generation X, the benchmark for this generation, and a relatively low score for generation Y's control group. However, to put this into perspective it should be noted that in generation X the amounts donated are higher in all conditions compared to generation Y when comparisons are made within treatments but across generations. Also, as for the treatment effects of the nudges in absolute terms, i.e. not relative to respective control groups, the personal experience treatment turns out to be most effective for both generations.

The high score for generation X´s control group may have inflated the overall control group (i.e. the aggregated control group), possibly resulting in dwarfing the results of both treatment groups. It is suspected that this causes the effect of the nudges on the amount donated to be low on average in the across treatment comparison. This suspicion is supported by the studies that show that behavioral nudges actually can be used to stimulate sustainable behavior which are discussed in section 2. Although statistical tests have shown that there is no sample clustering in the across treatment comparison based on the added socio-demographic variables, this high benchmark seems spurious. A new control group with participants from both generation X and generation Y could be collected to test whether the high score is due coincidence. In addition, in future research other control variables could be added to control for socio-demographic clustering in other areas. Examples of imaginable influences are the branch someone works in or someone's highest level of education. Yet another reason that may be underlying the high score for the control group is that essentially the control condition also has environmental context. Although it is formulated in a relatively abstract way, it can also trigger people to donate. It should therefore be noted that the control group is not a completely clean and contextless benchmark. Still, apart from assuming the observed effect to be non-existing, studies have also been conducted that conclude ineffectiveness, or even adverse effects, of nudges (e.g. Henkel, Seidler, Kranz, & Fiedler, 2019; Momsen & Stoerk, 2014). This shows that there is still a possibility that the negative effect on generation X observed in this study actually exists.

Relating the results to other literature, it strikes that this relatively low benchmark for generation Y goes against what was suggested by Ivanova et al. (2018) as well as by Berkup (2014). According to these studies, this generation should have a higher standard of sustainable behavior because of their upbringing in an era where sustainability is more central. However, considering the observed generational effects of nudging on the donated amount, a more positive effect for the younger generation makes perfectly sense. Both Böhm et al. (2020) and Fischer et al. (2004) suggest that people in nature tend to prefer lower costs for the benefits of their own generation at the expense of future generations, rather than higher costs to preserve for future generations at their own expense. Taking into account the years to come for generation Y compared to generation X, a greater (and positive) effect of nudges for the former fits the line of expectations.

Then, adding the probability of donating to the analysis, both the aggregated control group (i.e. generation X and Y combined) and the generation X control group are once again striking with their 96.6% and 100% probability scores respectively. Nevertheless, the results for the analysis regarding the donated amount and the analysis regarding the probability of donating, do not show any widely deviating results for the between treatment comparison. Where in the former the differences in donated amounts between control and both treatments were small, in the latter both treatments again show a difference in probability of only 5.5%. It is noteworthy that again, contrary to the results of the existing studies discussed in section 2, the probability of a participant donating is higher in the control group than in both treatment groups, indicating an adverse effect of nudges.

The results become even more interesting when both analyses for generational differences are combined. The difference between generation X's and Y's control groups in probability of donating is rather low (6.4%) as opposed to in the analysis that focused on the donated amounts (52.7%). Comparing probabilities of donating for both treatments in the generation X group with their respective control group, the results pale due the control group's 100% probability score. Still, the probability of donating within the samples for generation X, but also for generation Y, do not look disappointing in themselves. It is striking, however, that also for generation Y both treatments score a lower probability compared to their respective control group in the first place, but also that both treatment groups for generation Y score a lower donating probability compared to their equivalent in generation X. The latter result is even more striking considering the results of the earlier analysis on the donated amount: although for generation X the nudges seem to have an adverse effect on the amount that participants from this generation donated, the nudges did seem to have a positive effect on generation Y (i.e. the intensive margins of the treatments are much higher for generation Y when comparing to both generations own respective control group). Yet, contrasting probabilities of donating to the generations' respective control group, the differences are rather small (i.e. the extensive margins of the treatments are nearly equal for the generations when comparing to both generations respective control group). It seems contradictory that the difference in donated amounts deviates widely between generations whereas the probability of donating is rather close.

As a final contradictory result, it is noteworthy that in the analysis of donated amounts the nudges show mixed results, while there is agreement between the generations in the analysis on probability of donating. For the donated amounts, the personal experience treatment is the most effective of the two nudges in both generations. With the probability of donating, the personal experience treatment is more effective in generation X than the current problem treatment. With generation Y, this is the opposite. A caveat to the nudges is that although they are both clearly related to hampering climate change, they at the same time are entirely different. While the personal experience treatment only contains a textual trigger does the current problem treatment contain both a textual and a visual trigger (i.e. the graph). This could be seen as a combination of two different nudges. It is however unknown what the effect of the textual aspect and the visual aspect is separately.

Yet, despite the observed outcome regarding the non-effect of nudges in general that contradict earlier studies in the field; the theoretically non-sensible outcome for generation X's insensitivity to nudges, and the sensible outcome for generation Y's sensitivity to nudges which become ambiguous when the analysis on probability of donating comes in, it is important to notice that only two of the coefficients for relevant treatment variables are statistically significant ($\alpha = 0.05$). Hence the observed effects deserve more research in the future before they can actually contribute to the field and provide policymakers with insights for potential benefits of differentiated nudging between target groups that are subject to different generations. This additional research is even more desired since the ranksum tests for checking significant differences in effects across generations show that only within the control condition the effects on both generations differ significantly, whereas this is not the case for both treatment conditions; a result that was already implied by the regressions. Power analysis shows that the number of observations will have to be expanded considerably when rerunning the experiment. Yet, it is conceivable that this is due to an unrepresentative score of generation X´s control group either. After all, the closely spaced sample means with the across treatment comparison results that power analysis recommends a large number of observations to confirm that the observed effects are actually true. Nonetheless, for the between generations comparisons the sample sizes did not suffice either, which is (partly) due to time and monetary constraints as discussed in section 3.

In the end few significant effects of the nudges on both the amounts donated and the probability of donating were found to exist, both in general and related to generations. Yet, significant effects appear to exist between age and the amount donated. Such an effect is found in the between treatment comparison on aggregated samples (i.e. no generational separation) for the control group and for the current problem treatment. Still, a significant effect of age on the donated amount is in the across generations comparison only found in one sample: the current problem treatment for generation X. These results imply that nudges may have an age-dependent influence on the tendency towards sustainable behavior, but that it may be less black and white than having different effects on an entire generation. Nevertheless, this result may also be driven by having set the age boundaries incorrect for the generations.

5.2 Strengths and limitations

While the possibly inflated score for generation X's control group already has been discussed, a couple of limitations to the study can be pointed that may have caused the observed effects to happen. First, with the between generations comparison it turns out that the control variables denoting whether someone donated to a charity before and whether someone has children, are clustered in generational samples for all the experimental conditions (i.e. data on whether one has children and on whether one donated to a charity before is significantly different in generation X than in generation Y for all samples). For whether someone donated to a charity before it makes theoretically sense that people in generation X are more likely having donated to a charity before as they have different live contexts (Granovetter, 2005): they might have different perception on the world and hence they might have donating to a charity higher on their priority list compared to people belonging to generation Y. In concrete terms, however striking it is since this goes against expectations, statistical tests show that there is no significant difference in income between the two generational groups within the dataset. Still, there could be a difference in disposable income between generation X and Y. People in generation Y may, for instance, have repaid less on their mortgage, which means that they might have higher housing costs. The result is that they have less disposable income after fixed costs and therefore have less room to donate money. There is however not controlled for this in the experiment and hence no hard claims can be made on differences in disposable income between generations and its effect on donating to an environmental charity.

For having children as a control variable the clustering makes theoretically sense as generation Y starts at the age of 15. It is therefore likely (and observable in the data) that many more participants in generation X have children compared to in generation Y. This means that except for the generation one is born in solely, having donated to a charity before and having children might be alternative explanations for the amount people donated in the experiment. Yet, the above only indicates that in theory these variables can both be considered directly related to the generation one belongs to. It should be noted however that this is purely speculative and further research must be done for confirmation.

Additionally, as already mentioned may a one-off measurement, in the form of an online survey where participants are incentivized by a raffle of vouchers, not be the most valid measurement tool. Since the donation one does in the experiment is purely hypothetical, a discrepancy between stated and revealed preferences is likely and hence hypothetical bias might play part despite incorporation of a cheap talk script before the start of the actual survey (de Corte et al., 2021; N. Wilkinson & Klaes, 2012). For this reason there has been referred to *tendency towards* sustainable behavior rather than *actual* sustainable behavior in this study. Nevertheless, of the participants who approached me afterward, none of them could guess correctly what the purpose of this study is, meaning they still had no idea they had been nudged. This gives confidence that participants have been objective in providing their answers in the survey. Another comment to make here concerns the choice for a donation between €0 and €100. Perhaps even $100 is not an indispensable amount for most people, especially for generation X as explained above. It is also possible that generation X's donations are relatively higher because of this. One way to overcome this would have been to ask participants to donate a percentage of their income, which would have introduced relativity and controlled for differences in income. However, absolute amounts have been chosen instead because it is less abstract. If the abstract percentages were chosen, this would increase the chance that the task was not well understood by the less skilled and the results would also be biased, resulting in an unrealistic picture.

As a final remark, the extension of both generational groups by 7 years deserves an explanation as mentioned earlier. The generational groups, generations X and Y, have been taken for comparison. It may indeed be useful to analyze more than just these two generations. However, given the limited time and resources, it was not feasible to collect sufficient data on more than two generational groups. Yet the division between generations is not an exact science and can even overlap (Ivanova et al., 2018). Therefore, it is considered justified to extend both generations by 7 years. This extension was initially chosen to ensure that the number of respondents would be sufficient as the intention was to collect a large part of generation Y's data among students. At the time, the lower age limit of 15 was considered most appropriate. In retrospect, the data was collected from a much broader target group than students, resulting in that the lower limit of 15 is not strictly necessary. However, reaching a broader target group than a cluster of students may have benefitted this study's external validity.

Nonetheless, it should be noted that the external validity is still limited given the experimental design. Participants were recruited via social media accounts that concern both various private and corporate accounts. Although these are several accounts that have independent networks to a certain extent, independence of the participants is not to the extent required by a clean experimental design in scientific research where participants are recruited with more randomness. Moreover, as much participants as possible were recruited within a given time span whereas the proper way would be to pre-specify an amount of participants per sample to recruit.

6 Conclusion

Because climate change, largely man-made, is perhaps the world's greatest challenge of current times, behavioral change is urgent. Policymakers have agreed in recent decades that nudging policy can be used effectively for this purpose as a replacement for monetary incentives to make people behave more sustainably. This study aimed to examine whether there is a difference in sensitivity to nudges towards sustainable behavior between different generations. Generation X, pre-millennials and generation Y, millennials have been taken as the target group. Where first an effect of behavioral nudges was investigated on the basis of aggregated samples (i.e. no generational differentiation), it was found that on average the nudges have little to no effect on one's tendency for sustainable behavior. After dividing the data into generational samples, analyzing the donated amount the behavioral nudges were found to be effective in promoting the tendency to sustainable behavior among the millennials, but had an adverse effect among the pre-millennials. Yet, when the analysis of the probability of one donating after being exposed to certain nudge is contrasted to this, contradictions between intensive and extensive margins appear. In summary, the comparison concludes that the donating probability due nudges for both generations is nearly equal. Based on these extensive margins, the nudges appear to have similar effects on both generations. However, the effectiveness of nudges on the amount donated is negative for generation X while positive for generation Y when comparing to generations' respective control group, meaning that based on the intensive margins the effectiveness of nudges between the two generations deviates widely. These contradictory results together lead to the impossibility to draw an unambiguous conclusion. Unambiguous results would have contributed to insights for policymakers involved in nudging policies, in the sense that they can bring about sustainability with differentiated policy. This differentiation would help to implement tailor-made policies for different target groups which can increase effectiveness of policy and can be cost saving. Moreover, would it turn out that no generational differences in sensitivity exist, it prevents policymakers from bothering for differentiated policy. This is cost saving either. Nevertheless, this study has produced at least one result. Although nudges do not show a significantly different effect on generations, the amount of donation and thus the tendency towards sustainable behavior seems to be positively related to age.

As discussed at the beginning of this paper, many studies have shown that nudges are effective in promoting sustainable behavior. Generation Y's sensitivity to nudges towards sustainable behavior is therefore plausible. The adverse effect on generation X and the ineffectiveness of nudges in general, however, contradict these literature. It should be noted that this study is subject to several limitations and that most of this study's results are not statistically significant. Its findings are therefore not yet usable in practice. The suspected root cause that led to this is the measurement tool used which is sensitive to hypothetical bias. One conceivable consequence of this phenomenon is the remarkably high donation in the benchmark group of generation X. Still, several studies in the field of behavioral economics conclude on ineffectiveness on nudges and therefore the adverse effect on generation X may in fact exist.

Moreover, when interpreting the results one should be cautious anyway since only two different nudge treatments have been tested here on a relative small sample that is due time and monetary constraints not derived in a statistically clean manner. It is probable that the results may differ depending on the sample context and the type of nudge. It is open for future research to conduct a field experiment on a larger scale for the exploration of generational differences in actual sustainable behavior resulting from behavioral nudges. A proposal for such a research could be the study among hotel guests and towel reuse that Goldstein et al. (2008) conducted as discussed in section 2, because the generation to which a specific guest belongs can be traced through booking data.

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8 Appendix

8.1 Appendix A: Climate change – How it works and the consequences

Although outside the scope of this study, it is interesting what underlies climate change. It clarifies how human behavior has its devastating effect on the Earth and why change is urgent. Moreover, the consequences discussed here provide ground as well as context for the nudges constructed on behalf of the experiment.

How it works

Heat from the sun reaches our earth's surface, after which a large part of it is reflected directly back into space. The rest is absorbed by the earth and water surface and by greenhouse gases. The latter re-emits the heat in all directions within the atmosphere. It is this "greenhouse effect" that regulates the temperature on earth and thus makes life on earth possible (National-Academy-of-Sciences, 2020). However, this greenhouse effect has turned against humanity since the industrial revolution. The concentration of greenhouse gases has increased significantly since then, including the three main greenhouse gases: Carbon Dioxide (CO^2), Methane and Nitrous Oxide (US-Environmental-Protection-Agency, 2022a). The increase since pre-industrial times

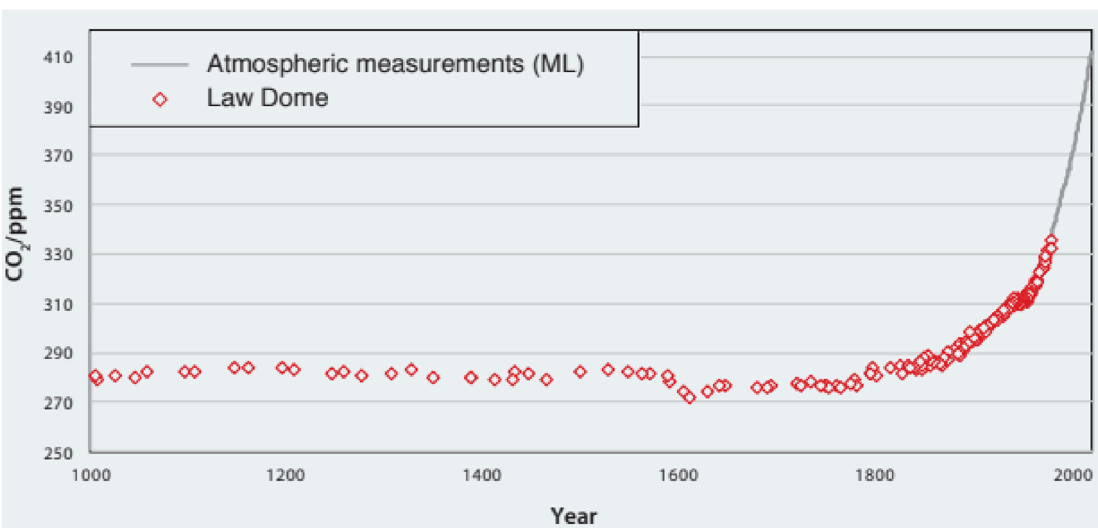

FIGURE 4. CO^2 CONCENTRATION IN THE EARTH ATMOSPHERE OVER THE PAST 1000 YEARS. NOTE: THE GRAPH SHOWS HOW THE CO^2 CONCENTRATION IN THE ATMOSPHERE HAS CHANGED OVER THE PAST 1000 YEARS (YEAR 1000 TO 2000), MEASURED IN PARTS PER MILLION (CO^2/PPM). DATA AFTER 1958, SHOWN BY THE GREY LINE (ML), ARE ATMOSPHERIC AIR MEASUREMENTS TAKEN AT THE MAUNA LOA OBSERVATORY LOCATED IN HAWAII. THE MEASUREMENTS BEFORE THAT TIME, REPRESENTED BY THE RED DOTS (LAW DOME), COME FROM AIR TRAPPED IN AN ICE CORE ON ANTARCTICA. THE GRAPH IS TAKEN FROM "CLIMATE CHANGE: EVIDENCE AND CAUSES: UPDATE 2020," BY NATIONAL-ACADEMY-OF-SCIENCES, 2020, THE NATIONAL ACADEMIES PRESS, P. B3 (HTTPS://DOI.ORG/10.17226/25733).

counts 40%, 150% and 20% respectively, from which for CO^2 more than half has occurred since the 1970s as Figure 4 illustrates (National-Academy-of-Sciences, 2020).

It becomes more concrete that human activities are the driver behind this when Figure 5 is consulted (US-Environmental-Protection-Agency, 2021). The figure shows that CO^2 is the major contributor to greenhouse gas emissions, which is the results of, for instance, combustion of fossil fuels for transportation, generating electricity and manufacturing processes, mainly for consumption purposes (National-Academy-of-Sciences, 2020; US-Environmental-Protection-Agency, 2021).

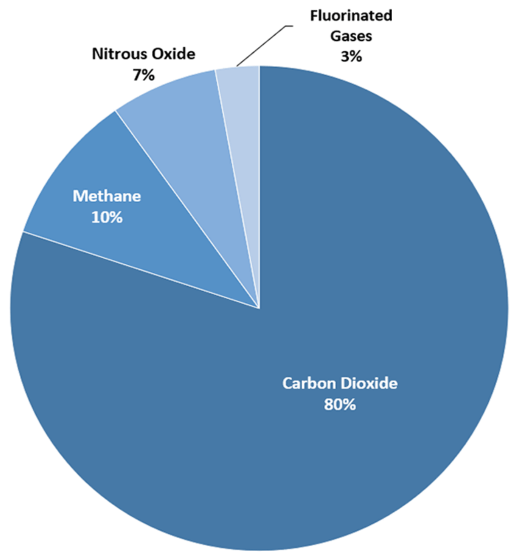

FIGURE 5. OVERVIEW OF U.S. GREENHOUSE GAS EMISSIONS IN 2019. NOTE: THE FIGURE SHOWS THE GREENHOUSE GAS EMISSION SHARE OF THE MOST IMPORTANT GREENHOUSE GASES EMITTED DUE HUMAN ACTIVITIES. IT CLEARLY FOLLOWS THAT CO^2 IS THE MAJOR CONTRIBUTOR TO GREENHOUSE GAS EMISSIONS. THE FIGURE IS TAKEN FROM "OVERVIEW OF GREENHOUSE GASES," BY US-ENVIRONMENTAL-PROTECTION-AGENCY (2021), *EPA*, (HTTPS://WWW.EPA.GOV/GHGEMISSIONS/OVERVIEW-GREENHOUSE-GASES)

This greenhouse effect is enhanced by changes in the soil surface. Deforestation and urbanization, for instance, change the reflectivity of sunlight on the earth surface, but also the melting of polar caps does, which in itself is a result of climate change and thus causes a snowball effect. As a consequence of this changing earth surface, the earth retains more heat on the surface, causing global warming either (National-Academy-of-Sciences, 2020; US-Environmental-Protection-Agency, 2022a).

The consequences

The consequences are enormous and felt worldwide. The continues rising of the global temperature leads water volume to increase and polar caps to melt, causing sea levels to rise. In the past century, the sea level has already risen 16 centimeters and the current forecast is an increase of another 40 to 80 centimeters by the year 2100. Still, even then the increase will not come to an end (National-Academy-of-Sciences, 2020). Eventually it will mean the end of their habitat for many who live in the lower areas. Though, not only life on land is affected. Also underwater are the effects noticeable. An increase in the amount of CO^2 in seawater changes the acidity, with major consequences for the underwater ecosystems. Species will die out, disrupting the food chain, potentially including that of human beings (National-Academy-of-Sciences, 2020; US-Environmental-Protection-Agency, 2022b; World-Commission-on-Environment-and-Development, 1987).

Another consequence is increasingly deviating weather from what is normal for the time of year. The same goes for extreme weather and natural disasters. Mild winters that disrupt ecosystems and summers with extreme heat and drought that have burned many acres of forest in recent years (US-Environmental-Protection-Agency, 2022b). In addition, the higher temperatures on Earth lead to a humid atmosphere. Combined with higher ocean temperatures, this provides ideal conditions for the strongest, longest lasting and most devastating hurricanes, even in places where this was unlikely in the past (National-Academy-of-Sciences, 2020).

Finally, the perhaps most drastic event of today's living cannot be ignored here: global pandemic (COVID-19). Disrupting ecosystems, for example through deforestation, leads animals to lose their habitat, meaning that they have to look for another place to live. The shrinking space causes both species extinction and the convergence of more animal species in a smaller habitat. This is a hotbed for (infectious) diseases (Xiao et al., 2020). In addition, animals change habitat as a result of climate change. More specifically, due extreme heat and drought (Jackson et al., 2014; Marazziti et al., 2021). This leads to more species coming together in a smaller habitat either. More species in a smaller habitat means less food and shelter available. The survival instinct of (wild) animals leads them to urban areas, where humans eventually become infected (Zang, Benjenk, Breakey, Pusey-Reid, & Nicholas, 2021). Many of the world's population today will attest that the global consequences were enormous. They are again caused (in part) by the human depletion of natural resources.

8.2 Appendix B: original survey texts (Dutch)

The survey has been carried out among Dutch public and hence in Dutch language. In the core text of this study its English translation has been presented. Yet, one might be interested in the original survey texts. Hence screenshots of the original texts of the nudges are presented below. Screenshots have been taken to show maximum authenticity to the reader.

FIGURE 6. SCREENSHOT OF THE CONTROL CONDITION IN THE ONLINE SURVEY.

FIGURE 7. SCREENSHOT OF THE CURRENT PROBLEM TREATMENT IN THE ONLINE SURVEY.

FIGURE 8. SCREENSHOT OF THE PERSONAL EXPERIENCE TREATMENT IN THE ONLINE SURVEY.

8.3 Appendix C: The control variables chosen

Age: Although data on this variable is necessary to assign the participants to their right generational group, it may happen that within a treatment there coincidentally is some clustering going on. For example, if only participants between the ages of 15 and 25 were assigned to a particular treatment, data on the entire group aged 26 to 42 would be missing. This may have implications for the results, which are worth discussing.

Gender: likewise as for age, it may happen that despite randomization there is some clustering with respect to gender. As existing literature shows that generally woman feel more responsible for pro-environmental friendly behavior than man (Berenguer, Corraliza, & Martin, 2005; Luchs

& Mooradian, 2012; Zelezny, Chua, & Aldrich, 2000) this could be a potential alternative driver for the results, other than the treatment itself.

Income: Intuitively income can be considered a quite obvious driver for the amount to donate to a charity: the higher one's income, the more money remains for other purposes, like donating, after primary needs are fulfilled. Still, talking about income is a taboo for many. To make talking about income more accessible and encourage people to share this information, this variable has been subdivided into income classes with class widths of €500. Nonetheless, the option to not share information on income is also included in the survey to avoid that people quit the survey out of inconvenience.

Having children or not: if one maintains the present behavior the earth becomes exhausted and the wealth of future generations is consumed by present generations (Strand et al., 2021; World-Commission-on-Environment-and-Development, 1987). This is typically something parents could worry about, whereas childless people do not. This control variable will therefore also be added.

Donated to a charity before or not: people who donate to charities more often may be more generous in their donations than those who do not. Again, clustering of donors within a certain condition may yield biased results. This possible effect can be determined by adding this control variable.

8.4 Appendix D: testing for the OLS assumptions on donated amount regression – aggregated data

1. The dependent variable, donation, has been measured in a range from €0 - €100, meaning that the assumption on measurement at interval level has not been violated.
2. As robust standard errors have been used for the OLS heteroscedasticity is not an issue.
3. When variables are omitted residuals may be correlated. To control for this several control variables have been added to the model. As the regressions indicate do the results for the model including and excluding the control variables not change much, hence the assumption on uncorrelated error terms is not violated.

4. Similarly, these little changing results imply that none of the independent variables is correlated with the error term.
5. A VIF-test shows that there is no independent variable correlated with another independent variable (VIF-test: VIF = 1.34 for both treatment variables). Also, the correlation matrix shows a highest correlation of -0.51, which implies no problematic correlation.
6. According to modern Gauss-Markov theorem the linearity assumption is not strictly necessary.
7. Normally distributed error terms are not a big deal at all for OLS to be valid. Yet, even more so since non-parametric ranksum tests have been used as robustness checks.

8.5 Appendix E: testing for the model assumptions on probability of giving regression – aggregated data

1. According to modern Gauss-Markov theorem the linearity assumption is not strictly necessary.
2. Even though heteroskedasticity often occurs in linear probability models, this does not form a problem as robust standard errors have been used (Woolridge, 2015).
3. When variables are omitted residuals may be correlated. To control for this several control variables have been added to the model. As the regressions indicate do the results for the model including and excluding the control variables not change much, hence the assumption on uncorrelated error terms is not violated.
4. Similarly, these little changing results imply that none of the independent variables is correlated with the error term.
5. A VIF-test shows that there is no independent variable correlated with another independent variable (VIF-test: VIF = 1.37 for both treatment variables). Also, the correlation matrix shows a highest correlation of -0.51, which implies no problematic correlation.
6. Normally distributed error terms are not a big deal at all for OLS to be valid. Yet, even more so since non-parametric ranksum tests have been used as robustness checks.

8.6 Appendix F: testing for the OLS assumptions on donated amount regression – generational data

1. The dependent variable, donation, has been measured in a range from €0 - €100, meaning that the assumption on measurement at interval level has not been violated.
2. As robust standard errors have been used for the OLS heteroscedasticity is not an issue.
3. When variables are omitted residuals may be correlated. To control for this several control variables have been added to the model. As the regressions indicate do the results for the model including and excluding the control variables not change much, hence the assumption on uncorrelated error terms is not violated.
4. Similarly, these little changing results imply that none of the independent variables is correlated with the error term.
5. A VIF-test shows that there is no independent variable correlated with another independent variable (VIF-test: VIF = 2.58, 1.73, 2.58 and 1.73 for the treatment 1 dummy for generation X, the treatment 1 dummy for generation Y, the treatment 2 dummy for generation X and the treatment 2 dummy for generation Y respectively). Also, the correlation matrix shows a highest correlation of -0.22, which implies no problematic correlation.
6. According to modern Gauss-Markov theorem the linearity assumption is not strictly necessary.
7. Normally distributed error terms are not a big deal at all for OLS to be valid. Yet, even more so since non-parametric ranksum tests have been used as robustness checks.

8.7 Appendix G: testing for the model assumptions on probability of giving regression – generational data

1. According to modern Gauss-Markov theorem the linearity assumption is not strictly necessary.
2. Even though heteroskedasticity often occurs in linear probability models, this does not form a problem as robust standard errors have been used (Woolridge, 2015).
3. When variables are omitted residuals may be correlated. To control for this several control variables have been added to the model. As the regressions indicate do the results for the

model including and excluding the control variables not change much, hence the assumption on uncorrelated error terms is not violated.

4. Similarly, these little changing results imply that none of the independent variables is correlated with the error term.
5. A VIF-test shows that there is no independent variable correlated with another independent variable (VIF-test: VIF = 2.96, 3.60, 2.93 and 3.58 for the treatment 1 dummy for generation X, the treatment 1 dummy for generation Y, the treatment 2 dummy for generation X and the treatment 2 dummy for generation Y respectively). Also, the correlation matrix shows a highest correlation of -0.22, which implies no problematic correlation.
6. Normally distributed error terms are not a big deal at all for OLS to be valid. Yet, even more so since non-parametric ranksum tests have been used as robustness checks.

8.8 Appendix H: testing socio-demographic clustering within samples

TABLE 11. TEST RESULTS RANKSUM TESTS FOR SAMPLE CLUSTERING

Tested samples	P-values	
AGGREGATED SAMPLES		
Control group – current problem treatment	Age: 0.711 Gender: 0.600 Donated before: 0.358	Having children: 0.466 Income: 0.504
Control group – personal experience treatment	Age: 0.779 Gender: 0.485 Donated before: 0.181	Having children: 0.517 Income: 0.831
Current problem treatment – personal experience treatment	Age: 0.909 Gender: 0.216 Donated before: 0.341	Having children: 0.778 Income: 0.305
GENERATIONAL SAMPLES		
Control group gen X – current problem treatment gen X	Age: 0.423 Gender: 0.730 Donated before: 0.225	Having children: 0.369 Income: 0.350
Control group gen X – personal experience treatment gen X	Age: 0.791 Gender: 0.571 Donated before: 0.852	Having children: 0.239 Income: 0.968
Current problem treat gen X – personal experience treat gen X	Age: 0.519 Gender: 0.820 Donated before: 0.293	Having children: 0.764 Income: 0.2981
Control group gen Y – current problem treatment gen Y	Age: 0.967 Gender: 0.298 Donated before: 0.739	Having children: 0.447 Income: 0.884
Control group gen Y – personal experience treatment gen Y	Age: 0.847 Gender: 0.665 Donated before: 0.146	Having children: 0.645 Income: 0.829
Current problem treat gen Y – personal experience treat gen Y	Age: 0.856 Gender: 0.142 Donated before: 0.258	Having children: 0.766 Income: 0.746
Control group gen X – control group gen Y	Age: - Gender: 0.756 Donated before: 0.000	Having children: 0.000 Income: 0.559
Current problem treat gen X – current problem treat gen Y	Age: - Gender: 0.292 Donated before: 0.000	Having children: 0.000 Income: 0.372
Personal experience treat gen X – personal experience treat gen Y	Age: - Gender: 0.887 Donated before: 0.002	Having children: 0.000 Income: 0.473

Notes: Test results for ranksum tests on socio-demographic clustering across samples. Ranksum tests show that having children and whether one donated before to a charity or not do differ significantly between generations when generational samples are compared within all three conditions. Age has been left out from ranksum tests when generational samples within a treatment have been compared since generation is subject to age. Significant difference in age between the samples is therefore obvious.