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Bachelor Thesis

2022 **Eva Skácelíková**

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Testing the Use of Choice Defaults to Stimulate Behavior of Dancers

Bachelor Thesis

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Declaration

1. I hereby declare that I have compiled this thesis using the listed literature and resources only.
2. I hereby declare that my thesis has not been used to gain any other academic title.
3. I fully agree to my work being used for study and scientific purposes.

In Prague on 02.05.2022

Eva Skácelíková

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Abstract

The following thesis presents an experiment examining the effect of choice defaults on stretching of dancers. Stretching is one of possible injury prevention tools. The topic of the thesis is motivated by the importance of injury prevention in efforts to reduce public and private financial burden. Costs linked with injuries are shared among individuals and public finance sector. They are one of the components of government expenditures in the healthcare sector. We explored a sample of 202 participants aged 9-17. The treatment group was enrolled in an after-class stretching club as a default. The control group was exposed to opt-in condition, and they could sign up for the club. The participation in a club was voluntary for both groups. We observed whether participants were enrolled in a club and whether they stretched after class. The data were collected twice each week for a period of month. Analysis showed that the enrollment rate was 17.8 percentage points higher for the treatment group. Stretching rate was also higher for the treatment group, it differed by 11 percentage points. This result was not always statistically significant which might be caused by several limitations of the experiment. Next, we observed a difference of 19.3 percentage points in the effect of age on probability to stretch. Probability to stretch was higher for older participants. Finally, results revealed a decline in probability to stretch over time. When the first and the last period are compared, probability to stretch decreased by 30.2 percentage points.

Keywords

behavioral economics, nudges, choice defaults, healthcare, injury prevention, long-term effects

Abstrakt

Tato bakalářská práce prezentuje experiment zkoumající efekt výchozích nastavení na protahování tanečníků. Protahování je jednou z možností, jak předcházet zraněním. Téma práce je motivováno důležitostí prevence zranění při snižování soukromého i veřejného finančního břemena. Náklady spojené se zraněním jsou sdíleny mezi jednotlivci a veřejným sektorem. Jsou jednou ze složek vládních výdajů ve zdravotnictví. Zkoumali jsme vzorek 202 účastníků ve věku 9-17 let. Experimentální skupina byla defaultně zapsána do protahovacího klubu. Kontrolní skupina měla možnost se do klubu přihlásit. Účast v klubu byla dobrovolná pro obě skupiny. Zaměřili jsme se na to, zdali jsou účastníci zapsáni v klubu a jestli se po lekcích protahují. Data byla sbírána dvakrát týdně po dobu 1 měsíce. Analýza ukázala, že míra zápisu do klubu byla o 17.8 procentních bodů vyšší pro experimentální skupinu. Míra protahování byla také vyšší pro experimentální skupinu, rozdíl byl 11 procentních bodů. Tento výsledek ovšem nebyl vždy statisticky významný, což mohlo být způsobeno limity studie. Dále, u efektu věku na míru protahování jsme pozorovali rozdíl 19.3 procentních bodů. Míra protahování byla vyšší pro starší účastníky. Konečně, výsledky odhalily pokles v míře protahování v čase. Když srovnáme první a poslední období, míra protahování se snížila o 30.2 procentních bodů.

Klíčová slova

behaviorální ekonomie, nudges, choice defaults, zdravotnictví, prevence zranění, dlouhodobý efekt

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1 Introduction

For EU countries, total government expenditures in the healthcare sector represent on average 7% of GDP (Eurostat, 2019). One of the components of these expenditures is financial burden associated with injuries. Injuries are linked with costs of medical treatment, costs of lost productivity and sometimes even lifetime costs (Corso et al., 2006). They are shared among individuals and public finance sector. Widely spread sedentary lifestyle, lack of physical activity, smoking and unhealthy diet worsen health and cause higher expenditures. Literature agrees that injury prevention is essential in efforts to reduce public and private financial burden (Eliakim et al., 2020; Hickey et al., 2014; King et al., 2013; Michaud et al., 2011).

In this thesis we focus on choice defaults and their use in preventing injuries that could further lead to lower expenditures for individuals as well for public sector. It could provide significant results for the implementation of nudges in the healthcare sector. To author's best knowledge no research studied possible applications of nudges in the healthcare sector with an aim to prevent injuries. Literature on default options has focused on many topics, such as promotion of healthy lifestyle and healthy diet (Arno & Thomas, 2016; Thaler & Sunstein, 2009; Venema et al., 2018), privacy on the Internet (Johnson et al., 2002), insurance and retirement plans (Kahneman, 2011; Madrian & Shea, 2001; Thaler & Sunstein, 2009).

By conducting a field experiment, the thesis aims to test if choice defaults could be used to stimulate behavior of dancers. It intends to apply choice defaults to motivate dancers to stretch after exercise by creating an after-class stretching club. Dance troupes, to which participants aged 9 to 17 enroll at the beginning of academic year, were randomly distributed into two groups. Control group was exposed to opt-in option; the participants were offered to sign up for the club. Opt-out option, defined as a possibility to quit the club, applied to the treatment group. Participation in the club was voluntary. Participants were observed for a period of month, twice each week and they were asked to note whether they stretched after a class or not. We aim to answer following research questions: What is the effect of the treatment on enrollment rate and on stretching rate? Does this effect persist in time? And what effect does age of participants have?

This thesis aims to contribute to the existing research, study the differences in opt-in and opt-out conditions and observe long-term effects of defaults. Specifically, it focuses on default options that require long-term participation rather than making one-off decision. Less attention was given to this topic in the literature (Venema et al., 2018). Next, adults instead of children were usually subject to research in the literature available and there has been little discussion about the introduction of nudges among sportsmen.

The experiment showed that the enrollment rate and the stretching rate were higher for the treatment group, however the results were not always statistically significant. The effect of age was statistically significant, the stretching rate was higher for age category old. Next, the stretching rate declined in time.

The thesis has the following structure. First, use of nudges in a context of economics and health is outlined, and summary of the existing literature is provided. Next, we describe design of the experiment, characteristics of the participants and methodology. In the following section, the hypotheses about the effects of default choices are presented. The results of the experiment are then introduced. Finally, we discuss the results and experiment limitations, and we provide a conclusion.

2 Use of Nudges in the Context of Economics and Health

Tools of behavioral economics are mostly associated with retirement plans, savings, insurance, and environmental issues. Less attention was given to their application in the healthcare sector. According to Eurostat (*ec.europa.eu, accessed 21.09.2021*), total government expenditures on healthcare in EU countries reached on average 7% of GDP in 2019. This corresponds with total expenditures of 983 billion of EUR per year. Corso et al. (2006) discuss a matter of lifetime costs of injuries in the US. They conclude that overall financial burden of injuries consists of lifetime costs, costs of medical treatment and costs of lost productivity.

Sedentary lifestyle, unhealthy diet, lack of physical activity, smoking and other factors contribute to the deterioration of health and therefore cause higher healthcare expenditures. At the same time, increasing life expectancy might deepen this problem. Literature on this topic agrees that prevention is essential in efforts to reduce public finance burden (Eliakim et al., 2020; Hickey et al., 2014; King et al., 2013; Michaud et al., 2011). In this thesis we focus on physical activity and injury prevention.

Donaldson et al. (2014), Eliakim et al. (2020) and Hickey et al. (2014) studied financial costs of injuries among professional hockey and football players. The sportsmen who were injured could not participate in the games. NHL players' income loss associated with injuries is estimated to 218 million dollars per year (Donaldson et al., 2014). The injuries did not only affect individual savings. Worse performance of players was reflected in the loss of 45 million pounds by average English Premier League team (Eliakim et al., 2020). Similar principles could be applied to others, not only professional sportsmen. Individuals who get injured lose their income and have excessive expenditures associated with medical treatment costs. At the same time, their employers lose profits. In addition, if children learn how to prevent injuries and if they are shown benefits of regular physical activity, consequences of their lack could be prevented earlier.

To conclude, injury prevention could result in lower health expenditures for individuals as well as for public finance sector. Costs of treatment, lifetime costs, salary losses and other expenses linked with lower productivity must be considered. Furthermore, physical activity itself enhances performance of individuals and provides several long-term health benefits (Penedo & Dahn, 2005; Reiner et al., 2013; Warburton

& Bredin, 2017). Nudges seem to be one of possible solutions owing to their efficiency and maintenance of free choice.

3 Literature Review

In this part of the thesis, literature on nudge theory and namely choice defaults are introduced. Conclusions from studies examining effects of nudges and differences in opt-in and opt-out conditions are presented. In particular, we focus on use of choice defaults in healthcare. Further, long-term effects and effects based on gender and age are reviewed.

3.1 Nudge Theory

Nudge theory is linked with names of Richard Thaler and Cass Sunstein and their work *Nudge: Improving Decisions about Health, Wealth and Happiness* (2009). The authors outline an approach of libertarian paternalism that aims to direct our decisions, stimulate desirable behavior, and simplify decision-making by slightly rephrasing a problem. At the same time, it is a legitimate instrument because it retains a freedom of choice and does not put any restrictions on available options.

Thaler and Sunstein work with a concept of two systems, Automatic System and Reflective System. Kahneman (2011), Stanovich (1999) and Sherman et al. (2014) apply similar approach of dual-process theory. The Automatic System is described as quick, intuitive, and cognitively easy mechanism which works autonomously on a base of emotions and heuristics. On the other hand, the Reflective system is used deliberately, and it involves critical and analytical thinking. Sherman et al. (2014) present a table of commonly listed properties of Type 1 (Automatic System) and Type 2 (Reflective System) processing:

Table 1: Properties of Type 1 (Automatic System) and Type 2 (Reflective System) processes (Sherman et al., 2014)

Type 1 processes	**Type 2 processes**
Holistic	Analytic
Automatic	Controlled
Relatively undemanding of cognitive capacity	Capacity demanding
Relatively fast	Relatively slow
Acquisition by biology, exposure, and personal experience	Acquisition by culture and formal
Parallel	Sequential
Evolutionarily old	Evolutionarily recent

Implicit	Explicit
Often unconscious or preconscious	Often conscious
Lower correlations with intelligence	Higher correlations with intelligence
Short-leashed genetic goals	Long-leashed goals that tend toward personal utility maximization

Kahneman (2011) suggests that in general people tend to rely more on the Automatic System and that it is usually the first one to provide solutions to problems. To demonstrate how information processing vary for the Automatic and the Reflective System, The Cognitive Reflection Test developed by Frederick (2005) can be used. It consists of three questions:

(1) A bat and a ball cost \$1.10 in total. The bat costs \$1.00 more than the ball. How much does the ball cost?

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?

(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? (Frederick, 2005)

Intuitive answers evoked by Automatic System first come to mind for most individuals: 10 cents, 100 minutes, and 24 days. However, these answers are wrong and only when Reflective System is engaged, correct answers of 5 cents, 5 minutes and 47 days can be given. According to Frederick (2005) 33% of the participants did not solve any problem while mere 17% answered all the questions correctly. Furthermore, majority of individuals who scored 3 out of 3 questions admitted that they had thought about the other answer at first.

Due to the conflict of the two systems, as well as insufficient attention and inertia, individuals often fail to recognize the most advantageous opportunity, stick to their preferences or further act in compliance with their decision. Thaler and Sunstein claim that nudges can compensate for some of these deficiencies (Thaler & Sunstein, 2009).

They developed a concept of choice architecture which describes a process of creating a design of a choice problem. A nudge is defined in the following way:

"A nudge, as we will use the term, is any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid. Nudges are not mandates. Putting the fruit at eye level counts as a nudge. Banning junk food does not." (Thaler & Sunstein, 2009)

One of the suggested nudge designs are choice defaults. Default is a predefined option which is automatically selected when nothing is done.

3.2 Choice Defaults

Literature on default choices focuses on many various topics and areas in which the policies are implemented. Many authors demonstrated how default choices might improve health, transform sedentary lifestyle or promote healthy diet (Arno & Thomas, 2016; Radnitz et al., 2013; Thaler & Sunstein, 2009; Venema et al., 2018). Others focused on environmental issues (Pichert & Katsikopoulos, 2008; Wagner & Toews, 2018) and on privacy on the Internet (Johnson et al., 2002). Significant portion of the literature covers topics of insurance and retirement plans (Kahneman, 2011; Madrian & Shea, 2001; Thaler & Sunstein, 2009). Some examples of studies on choice defaults are outlined in this section.

An application of choice defaults could be demonstrated by a research on organ donation conducted by Johnson and Goldstein (2003). The authors showed the importance of a setup of default options by focusing on strategies which countries adopted when seeking potential organ donors. Two alternatives were recognized. Opt-in condition meant that people could register to become organ donors. If they did nothing, they were not registered. Second was opt-out condition standing for a situation when all the people were enrolled unless they intentionally quit the program.

To compare effective consent rates to become an organ donor of several European countries, the authors used data from national registers. Austria, Belgium, France, Hungary, Poland, Portugal, and Sweden are countries with a presumed consent law (opt-out default). The effective consent rate was 85% or higher. In contrast with this number stands the rates for Denmark, the Netherlands, the UK and Germany, countries with opt-in policy. The consent rate was at most 27.5%. We can see that similar countries, such as Austria and Germany significantly differed in the number of potential organ donors. The rates were 99.9% for Austria and 12% for Germany. The study concludes that countries with opt-out policy have significantly higher rate of organ donation which results in greater number of lives saved each year.

401(k) is U.S. retirement plan system. Formerly, opt-in condition was valid, and employees had to actively enroll in the 401(k) plan. In 1990s automatic enrollment was first introduced. Some companies adopted opt-out policy and enrolled all their employees in 401(k) plan with a possibility to leave the plan. According to Madrian and Shea (2001) participation rates rose from 37.4% in 1998 (before the introduction of automatic enrollment) to 85.9% in 1999 (when automatic enrollment was introduced). Choi et al. (2004) reported a surge in participation rates up to 90%. Additionally, the opt-out rates grew only by 0.3-0.6 percentage points after the introduction of automatic enrollment (Thaler & Sunstein, 2009).

Other studies confirm increased participation rates in 401(k) plans with automatic enrollment and greater savings for individuals resulting from it. However, the authors also mention possible drawback of inconveniently selected default investment strategy which might on average outweigh the advantages of default enrollment and higher participation (Benjamin & Laibson, 2003; Choukhmane, 2021; Poterba et al., 1996). Thaler and Sunstein (2009) claim that default investment strategies tended to be conservative with a saving rate of 2-3%. The employees did not change a default setting even though many of them had selected more aggressive strategies when a default option had not been offered. Benjamin and Laibson (2003) indicate that traditional economic variables, such as saving rate, are for consumers of a negligible significance compared to nudges. Therefore, in this case, setting of choice defaults deeply affects savings of individuals.

Another study, conducted by Wagner and Toews (2018), focused on reducing consumption of plastic straws. The authors evaluated the effectiveness of a policy introduced in 2018 in the city of San Luis Obispo in California. The city banned restaurants and bars from freely providing plastic straws. Default changed and customers were given the straws only upon request. The authors gathered 133 questionnaires filled in by owners or managers of businesses assessing number of plastic straws consumed, changes that happened after the policy was introduced and subjective feelings about the policy. The results showed that switching the default was simple, cheap and did not anyhow restrict freedom of individuals. The authors indicated that most companies were not economically affected. Some of them even reported a decrease in costs. On average, consumption of plastic straws decreased by 32%.

To conclude, literature on choice defaults demonstrated that choice defaults are suitable for policy interventions. The effects of opt-out conditions are significantly higher than of opt-in policies. Furthermore, as Pichert and Katsikopoulos (2008) claim, the difference is more evident when individuals know little about the topic and when the problems involved are complicated. The authors agree with Johnson and Goldstein (2003) and Thaler and Sunstein (2009) that forced choices without default options have similar results to opt-out condition and are definitely better solutions than opt-in condition.

3.3 Choice Defaults in Healthcare

Implementation of choice defaults in healthcare focuses on two main areas. The first one examines promotion of healthy diet and the second one concentrates on physical activity, transformation of sedentary lifestyle and obesity prevention.

3.3.1 Healthy Diet

Interventions supporting healthy diet choices include the following: positioning healthy food near the counter and to most frequented places in a supermarket or canteen, attractive labeling, and informing about the benefits of eating vegetables and fruit. Marcano-Olivier et al. (2019) observed consumption of fruits and vegetables at 4 different school canteens in North Wales. The consumption was nudged by attractive names and labels and by offering vegetables before the entry course and fruits as first option instead of a dessert. They collected data for 3 weeks using cameras and recording food choices of students. During the experiment, increased consumption of fruits, vitamin C and fiber was monitored for the treatment group of 86 children compared to the control group of 90 children where no change was observed. No significant differences were found for consumption of vegetables.

Mistura et al. (2019) applied different approach. They added fresh vegetable options next to hot meals instead of placing them just at a salad bar. The authors compared baseline periods of two weeks with intervention periods of three weeks for a school cafeteria in Canada. The data was recorded by researchers. The study demonstrated a positive trend in vegetables consumption during the intervention periods, however the results were not statistically significant due to many limitations of the study.

Another research aimed at determining proportion of healthy food choices purchased at a kiosk at a railway station in the Netherlands. Over period of 4 weeks, healthy food choices were placed next to the checkout counter. The data was compared with baseline period before the experiment. The results showed a rise in a proportion of healthy products sold when the nudge was applied (Van Gestel et al., 2018).

Eventually, meta-analysis on healthy lifestyle choices done by Arno and Thomas (2016) concluded that, on average, nudges increased healthy consumption options by 15.3%.

3.3.2. Physical Activity, Sedentary Lifestyle and Obesity Prevention

In their longitudinal study on reducing sedentary behavior at work, Venema et al. (2018) examined stand-up working rates in a governmental organization. In total, 606 employees participated in the experiment. At work employees are not assigned a desk to work at but they can choose a different desk every day. Desks have two positions, sitting and standing working height. For two weeks the tables were placed into standing working height as a default. Researchers noted the number of employees working at sit-stand desks, position of a table and gender of an employee. They also observe long-term effects of this intervention. Stand-up working rate rose from 1.82% to 13.13% during the intervention period.

In their meta-analysis, Landais et al. (2020) aimed attention at choice architecture designs in general. They examined studies focusing on promotion of stair use, physical activity, and less sedentary working style. According to the authors, 67.6% of 88 studies in total presented positive effect of choice architecture intervention on behavior. They specify, that for 47.1% this effect remained significant when a nudge was removed.

Physical activity plays an essential role for the health of individuals. Radnitz et al. (2013) recognizes it as one of key features in preventing obesity. In addition, in the past decade, professional as well as recreational sportsmen have not only been interested in physical activity itself but also in stretching (Amiri-Khorasani et al., 2011; Peck et al., 2014; Tallat et al., 2018). Studies showed that stretching after exercise brings several benefits, such as injury prevention, better flexibility and increased joint range of motion (Behm et al., 2021; Ko et al., 2020; Medeiros & Martini, 2018; Tallat et al., 2018). Therefore, stretching could enhance performance and support healthy lifestyle. Despite all the benefits, people often do not stretch after exercise. No relevant studies focusing on interventions that would encourage stretching were found. This thesis aims to fill in this gap in research by evaluating the effectiveness of choice defaults in stimulating stretching after exercise.

3.4 Long-term Effects and Effects Based on Age and Gender

Recently, significant proportion of research on nudges focused on their long-term effects. Venema et al. (2018) studied stand-up working rates by setting sit-stand desks to default standing height. This intervention increased the rates from 1.82% to 13.13%. Two weeks after removal of the nudge the number declined to 10.01%. Two months later the stand-up working rate was 7.78% which is still significantly higher than before the experiment.

Another study examining energy utilization showed that 35% to 55% of decrease in energy consumption caused by a nudge still endured after the nudge was removed (Brandon et al., 2017). Likewise, for 4 weeks, Van Gestel et al. (2018) did not observe any significant fluctuations in increase in healthy product sales that were stimulated by placing healthy options next to the checkout counters.

Contrarily, nudges might have only limited long-term or spillover effects. Individuals might get used to a nudge, pay less attention to it, overcome initial inertia or become less motivated over time (Sunstein, 2017; Van Rookhuijzen et al., 2021). Inconsistencies in studies on long-term effects of nudges might stem from different environments and various types of behavior observed. Further, some experiments require permanent participation while others aim for stimulating infrequent decisions.

When different reactions to nudges related to age differences or comparison of children and adults are concerned, no relevant study was found. Experiments examining effects of nudges on children focus mostly on interventions at school canteens aiming at increasing consumption of fruits and vegetables. Marcano-Olivier et al. (2019) observed a significant rise in consumption of fruits after the intervention. On the other hand, a study conducted by Mistura et al. (2019) did not provide clear conclusion. Nonetheless, many experiment limitations were presented by the authors. Other studies supported the significance of nudges among children (Sutter et al., 2015; Zhao et al., 2021).

Finally, in their study on choice of courses at work, Borghans and Golsteyn (2014) found that default options were selected three times more often than other courses. They also concluded that women pick default courses more often than men. However, this might not be a general pattern since no other research focused on gender differences in the application of nudges.

This thesis aims to fill gap in research on choice defaults. In particular, it focuses on use of choice defaults in encouraging stretching after exercise, topic for which is available literature very limited. It could provide results important for injury prevention that could be utilized in the healthcare sector. The thesis also aims to examine persistence of the effect of choice defaults that require long-term participation rather than making one-off decision. Finally, it targets children to whom was likewise given less attention in the research.

4 Experimental Design

In this part we outline the experimental design, treatment assignment method and describe characteristics of a sample.

Field experiment was conducted to test whether choice defaults could be applied in healthcare sector as a stimulus for injury prevention. Specifically, dancers were motivated to stretch after class by introduction of a 5-minute after class stretching club. Choice defaults were employed as a nudge and as means of determining whether the participants will or will not be enrolled in the club as a default. For the experiment, dance school based in Prague was selected. At the beginning of the academic year participants enrolled at dance troupes that are a leisure-time activity.

4.1 Treatment Assignment

The treatment was assigned on a level of troupes. In general, individuals from different troupes do not know each other and do not meet. Two different age categories of troupes were observed. Taking into account number of individuals in a troupe and age category into which the troupe belongs, the troupes were randomly assigned a treatment. Half of the troupes in each age category was assigned to the control group and the other half to the treatment group.

The treatment group was exposed to opt-out option. All participants were signed up for the club as a default and they could sign out by crossing their names out of the table. To the control group, opt-in option was applied, and they were offered the opportunity to join the club. The participants could freely join or leave the club during the experiment.

4.2 Sample

12 troupes with a total number of 202 individuals were observed. The troupes were further sorted by age of the participants into two categories. Category young contains children aged 9 to 14 and category old participants aged 12 to 18. These two categories were evenly distributed between the treatment and the control group. There were only 6 boys participating in the experiment however this fact was anticipated because the experiment focuses on dance classes that are attended by girls more

frequently. Table 2 summarizes sample distribution and Table 3 presents characteristics of the troupes.

Table 2: Sample distribution

	Treatment group	Control group	Total
Troupes	6	6	12
Young	3	3	6
Old	3	3	6
Participants	101	101	202
Girls	96	100	196
Boys	5	1	6
Young	49	47	96
Old	52	54	106

Table 3: Characteristics of troupes

Troupe	Group	Number of participants	Number of boys	Age category	Age min	Age max
2A	Treatment	28	2	Young	10	14
2B	Treatment	16	1	Young	9	12
2C	Treatment	5	0	Young	11	14
2D	Control	12	0	Young	10	13
2E	Control	17	0	Young	9	13
2F	Control	18	1	Young	10	13
3A	Treatment	26	2	Old	12	17
3B	Treatment	21	0	Old	12	16
3C	Treatment	5	0	Old	15	18
3D	Control	28	0	Old	13	17
3E	Control	7	0	Old	13	15
3F	Control	19	0	Old	13	17

There were also 11 teachers involved in the experiment who led the classes and collected data. They were given clear instructions and were asked not to motivate or discourage participants beyond the bounds of the experiment since different approaches of teachers could modify final results. If a third person was to attend classes natural environment could be disturbed and participants might change their behavior.

4.3 Procedure

The experiment consisted of introduction of an after class stretching club. It was presented as being voluntary and it was not considered part of a class. Even if participants signed up for the club, they were not obliged to attend it. Those who wanted to attend the club were asked to stay in the studio for at least five minutes after the class ended and to stretch after exercise. Participants had not been informed in advance that they were part of an experiment since this information could modify their behavior and therefore alter the results.

The experiment started with a presentation of the club. The teachers gave participants instructions about the principles of the club. The importance and the effects of stretching were mentioned as well. Next, the participants were given a table which enabled them to enroll to the club in a way determined by the treatment the troupe was exposed to. The participants from the control group were asked to write their names down to join the club whereas the participants from the treatment group were all signed in as a default and they could cross their names out if they did not want to participate. The tables later served as an attendance sheet. This introductory information was repeated to the children who were not present at the first class.

Then, after every class participants who attended the club and did the stretching for at least five minutes could mark their attendance. Furthermore, to avoid errors caused by forgetfulness of the participants, teachers noted the number of those who stretched as well. However, these two numbers did not differ because teachers did not do the observation independently and they rather reported the number from the attendance sheet which was marked by the participants.

When the experiment ended, the participants were informed about its aims and were further encouraged to continue stretching after classes.

4.4 Data

Dance classes take place two times a week. The data were collected for a period of a month, twice each week. In total, 8 observations were made for each troupe. For every individual data observed were the attendance in a class, whether they joined the club or not and participation in the club (stretching after class). Time that had passed since the beginning of the experiment was monitored as an order number of the class.

5 Methodology

In this section, variables observed in the experiment are described, as well as methods used to analyze the data and assumptions made on the structure of data.

5.1 Dependent Variables

Enrollment in a club (*Enrol*)

Enrol is a binary variable that signifies whether an individual is enrolled in a club or not. For the treatment group, this variable had value 1 as a default because all the participants were enrolled and for those who did not want to participate, the value changed to 0. Enrollment rate is a proportion of those enrolled in a club out of the whole group.

Stretching after class (*Stretch*)

Dependent variable *Stretch* is a binary variable that gains value 1 if an individual stretched after class and value 0 if they did not. It is a probability that an individual will stretch after class, in other words, probability to stretch.

Stretching rate is defined as a proportion of participants who stretched after class and of those who attended the class.

5.2 Independent Variables

ID (*Id*)

Variable *Id* serves as an identifier of each individual.

Order number of the class (*Time*)

Variable *Time* represents the amount of time that has passed since the beginning of the experiment. It is a factor variable attaining values from 1 to 8. The values determine order number of the class during which the data was collected. It is an indicator of motivation to stretch which participants have and that varies in time.

Attendance (*Attend*)

Attend is a binary variable indicating if an individual attended a class (value 1) or not (value 0). Attendance rate is defined as a proportion of participants who attended a class and of those who are enrolled in the class.

Treatment (T*reat*)

We introduce dummy variable *Treat* for the treatment. It equals to 1 for the treatment group and 0 for the control group.

Troupe (*Troupe*)

Data about 12 different troupes were collected and therefore we add this factor variable to control for the effects that might occur from non-identical approach of teachers and other factors influencing the troupes. We expect some teachers to be slightly more or less supportive than the others. Moreover, a design of a studio or time of day (afternoon or evening) at which the class takes place might affect the results as well.

Variable *Troupe* was further transformed into a binary variable A*ge* based on an age category to which the troupe belongs. For younger participants, aged 9 to 14, this variable gains value 1 and for older individuals from 12 to 18 years of age, it has value 0.

In the analysis we did not introduce any variable controlling for gender since 97.03% of the participants were girls and only 2.97% boys. The sample was restricted to dancers and dance classes are in general attended by girls rather than by boys. Therefore, we do not find it limiting in this case. As a robustness check, Table A1 in the Appendix shows main results of the experiment for a subsample of girls. The results do not differ from those obtained in the analysis.

5.3 Data Analysis

Prior to the analysis missing or extreme values were excluded from the sample. For one of the troupes, the data was missing for the last observation. Further, all the observations for which an individual did not attend a class were not used for the analysis of the treatment effect.

Initially, standard statistical tests and procedures were used to compare the treatment and the control group, to carry out the randomization check and to describe the data. We concentrated on size of troupes and age of participants. We also analyzed attendance rates for the treatment and the control group to ensure that the treatment effect is not caused by higher attendance in one of the groups. Following research questions asked in the introduction, the data analysis first focuses on effects of choice defaults and differences in opt-in and opt-out options for pooled data and then it examines persistence of the treatment effect.

We employ probit model estimated by maximum likelihood estimation to analyze the effects of choice defaults. We compute average marginal effects (AME). First, number of participants enrolled in a club is compared for the treatment and the control group. Data was restricted to the first period because this effect is fixed over time. The model looks as follows:

$$P(enrol_i = 1|treat_i) = G(\beta_0 + \beta_1 treat_i) \qquad (1)$$

$$with \quad G(z) = \int_{-\infty}^{z} g(v)dv$$

$$g(z) = 2\pi^{-\frac{1}{2}} \exp\left(\frac{-z^2}{2}\right)$$

$$z = \beta_0 + X\beta$$

To evaluate the treatment effect, the following model is estimated for the whole dataset as well as for each period separately.

$$P(stretch_i = 1|treat_i) = G(\beta_0 + \beta_1 treat_i) \qquad (2)$$

To improve the precision of the estimation and to decrease variance, we add explanatory variables and interaction terms to the model.

$$P(stretch_i = 1|treat_i, age_i) = G(\beta_0 + \beta_1 treat_i + \beta_2 age_i) \qquad (3)$$

$$P(stretch_i = 1|treat_i, age_i) = G(\beta_0 + \beta_1 treat_i + \beta_2 age_i + \beta_3 treat_i * age_i) \qquad (4)$$

To observe long term effects of choice defaults and evolution in time we add factor variable *Time* to the regression. It is represented by one binary variable for each period except for the first one which serves as a base value. We also estimate this model using variable *Time* as a numeric variable. Panel data estimation cannot be used since all the variables except for the dependent variable S*tretch* are constant over time. We use this model:

$$P(stretch_i = 1 | treat_i\, , age_i, time_i) = G(\beta_0 + \beta_1 treat_i + \beta_2 age_i + \beta_3 time_i) \qquad (5)$$

Finally, to assess if the treatment and the control group evolve similarly over time, interaction term of time and treatment is added to the model. The same is done for variable age.

$$\begin{aligned} P(stretch_i &= 1 | treat_i\, , age_i, time_i) \\ &= G(\beta_0 + \beta_1 treat_i + \beta_2 age_i + \beta_3 time_i + \beta_4 treat_i * time_i) \qquad (6) \end{aligned}$$

$$\begin{aligned} P(stretch_i &= 1 | treat_i\, , age_i, time_i) \\ &= G(\beta_0 + \beta_1 treat_i + \beta_2 age_i + \beta_3 time_i + \beta_4 age_i * time_i) \qquad (7) \end{aligned}$$

5.4 Assumptions

We work with independently pooled data. Every period, a subsample is drawn from our sample, based on the attendance of participants. We only consider those who attended a class in a given period. Therefore, we observe different sample in every period.

Additionally, we focus on 12 different troupes, and we repeat observations for them. We obtained several observations for each individual and we also want to eliminate characteristics specific for each troupe that might influence the data. For that reason, we employ clustered standard errors based on clusters of troupes to test for statistical significance. Clustered standard errors are used for the analysis of pooled data. For the models where dataset is restricted only to certain periods, standard errors are employed.

Since a probit model is used to test model restrictions, we apply the likelihood ratio test and as a goodness-of-fit measure we work with McFadden's pseudo R^2.

6 Hypotheses

Hypotheses about the results of the experiment based on existing literature are presented in the following part.

Hypothesis 1

When the treatment and the control groups are compared, more participants will be enrolled in a club in the treatment group.

Hypothesis 2

Stretching rate will be higher for the treatment group.

Literature review provided a strong support for these two hypotheses. Participation rates differed by 80 percentage points in the case of organ donation. Enrollment in 401(k) plan increased from 37.4% to 85.9%. Finally, stand-up working rates augmented from 1.82% to 13.13%. (Johnson & Goldstein, 2003; Madrian & Shea, 2001; Venema et al., 2018) We assume that if more individuals are enrolled in a club, greater number of them will stretch.

Hypothesis 3

Over time, there will be a significant decline in the stretching rate for both groups.

The reviewed evidence suggest that for nudges which require long-term participation effects will decrease over time (Sunstein, 2017; Van Rookhuijzen et al., 2021; Venema et al., 2018b).

Hypothesis 4

Age category of participants will not have a significant effect on the stretching rate.

As explained earlier, no relevant study examining age-related differences in the effects of nudges was found. However, several studies observed effects of nudges on children. (Marcano-Olivier et al., 2019; Sutter et al., 2015; Zhao et al., 2021).

7 Data, Results

In this part of the thesis results of the experiment are presented. First, randomization check is done. Next, treatment effect is evaluated. We focus particularly on enrollment rate, stretching rate and persistence of the effect in long term.

7.1 Randomization Check

This section aims to verify whether randomization was done correctly. It compares values of variables for the treatment and the control group that were measured before the treatment was introduced. Variables of interest are number of participants in a troupe and age of participants. The variables were stable during the experiment. We assume that the two groups are comparable, and no selection bias is present if values of these variables do not significantly differ. Therefore, we can estimate the effect of the treatment.

Troupes were randomly assigned a treatment. Number of participants in a troupe and its age category were considered. Table 4 shows that sizes of troupes did not significantly differ for the treatment and the control group (p-value = 1). On average, there were 17 participants in each troupe.

Table 4: Randomization check

	Treatment group				Control group						
	Min	Mean	Max	Age0	Min	Mean	Max	Age0	Diff in means	P-value	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
N in a troupe	5	16.833	28		7	16.833	28		0	1	12
Age category				0.515				0.535		0.764	1597

Comparison of the treatment and the control group in terms of number of participants in a troupe and age. Columns 4 and 8 display proportion of participants that belong to age category old in each group. Column 9 shows a difference in means (difference between columns 6 and 2). Column 10 Fisher test p-value associated with column 9.

The groups were also similar in terms of age categories. There were 49 participants belonging to category young in the treatment and 47 in the control group. 52 participants from category old were in the treatment group compared to 54 participants from the control group. Associated Fisher test p-value is equal to 0.764

(Table 1). Thus, we can assume that the randomization was done correctly, and the groups were on average the same prior to the treatment introduction.

7.2 Effects of the Treatment

7.2.1 Enrollment Rate

First, number of participants enrolled in a club is analyzed. It is fixed over time. No participant modified their initial choice after it was made. In other words, once participants opted in a club, all of them remained enrolled.

Enrollment rate was in general high, exceeding 80% for both groups. It was higher by 17.8 percentage points for the treatment group (Table 5). This difference is statistically significant with a p-value lower than 0.001. Interestingly, only one individual from the treatment group opted-out from the club. On the contrary, 6 participants from the treatment group who did not stretch after any class remained enrolled. All individuals from the control group who were enrolled in a club stretched at least once.

Table 5: Enrollment, attendance and stretching rate

	Treatment group Mean (1)	Control group Mean (2)	Diff in means (3)	P-value (4)	N (5)
Attendance rate	0.751	0.723	0.028	0.232	1597
Enrollment rate	0.990	0.812	0.178	<0.001	1597
Stretching rate	0.725	0.615	0.11	<0.001	1178

Further, the effect of the treatment is statistically significant (p-value <0.001) in determining enrollment rate when a probit model is used (Table 6, col. 1). An individual from the treatment group has on average probability of being enrolled higher by 21.4 percentage points than an individual from the control group.

Table 6: Model 1 – effect of treatment on enrollment rate

Dependent variable: Enrol	
	(1)
(Intercept)	0.885***
	(0.144)
Treat	1.445***
	(0.340)
AME Treat	0.214
	(0.060)
N	202
Pseudo-R^2	0.165

*Dataset restricted to period 1. AME: average marginal effect. Significance codes: 0.001*** 0.01** 0.05*.*

7.2.2 Stretching Rate

In this section we focus on the analysis of pooled data. Later, we will evaluate persistence of the effect in time. As we have shown, the treatment and the control group have on average the same characteristics. Therefore, to estimate average treatment effect, we can first use mean values of variable *Stretch*. Stretching rate is on average 11 percentage points higher for the treatment group, it is 72.5% for the treatment and 61.5% for the control group (Table 5). The result is statistically significant (p value <0.001).

Probit model (Table 7, col. 1) provides a result that is no longer statistically significant when clustered standard errors are applied. P-value equals 0.371. Average marginal effect of treatment is 10.9%.

Next, variable *Age* is added to the model. This model is preferred by likelihood ratio test to more restricted model 2. On average, probability to stretch is higher by 19.3 percentage points for individuals who belong to age category old (Table 7, col. 2). The effect of age category is statistically significant at 5% significance level (p-value = 0.047) however the treatment effect is not statistically significant (p-value = 0.280).

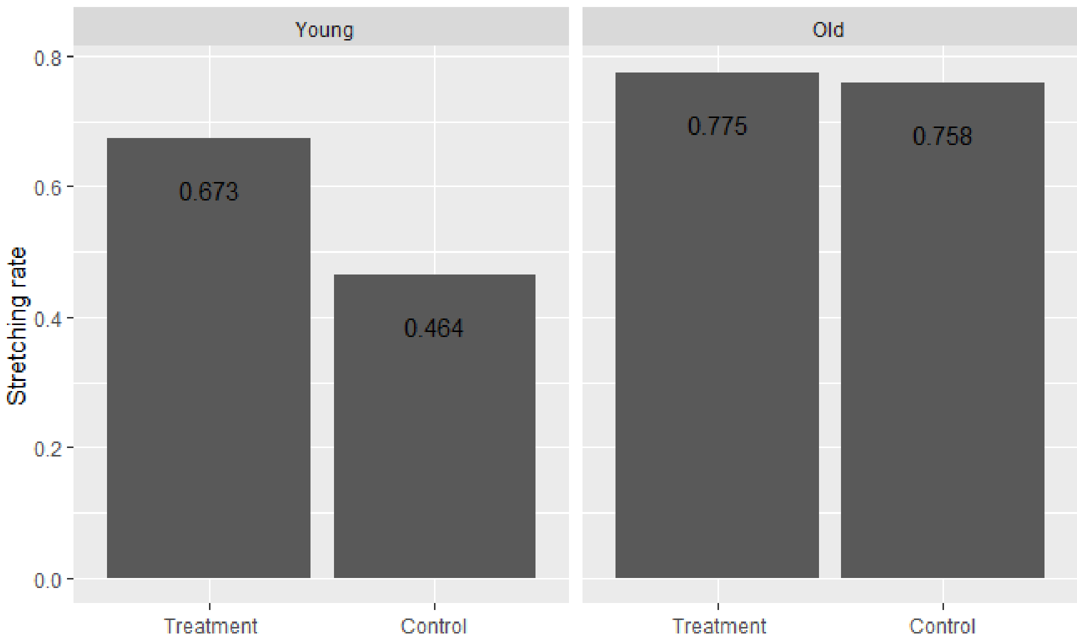
To estimate whether the treatment has similar effect on both age categories, we add an interaction term of variables *Treat* and *Age0*. Its effect is negative but it is not statistically significant with p-value equal to 0.367. Figure 1 summarizes probabilities to stretch estimated by this model (Table 7, col. 3). Probability to stretch is higher for the treatment group in both cases. The difference is larger in the control group where category young has 46.4% probability to stretch and category old a probability of 75.8%.

Table 7: Effect of the treatment for pooled data

Dependent variable: Stretch					
				Young category	Old category
	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.292	0.023	-0.090	-0.090	0.699***
	(0.242)	(0.239)	(0.255)	(0.255)	(0.140)
Treat	0.306	0.314	0.539	0.539	0.057
	(0.342)	(0.291)	(0.472)	(0.472)	(0.252)
Age0		0.549*	0.789**		
		(0.277)	(0.292)		
Age0*Treat			-0.482		
			(0.535)		
AME Treat	0.109	0.108	0.109	0.204	0.018
	(0.120)	(0.097)	(0.089)	(0.162)	(0.076)
AME Age0		0.193	0.195		
		(0.103)	(0.097)		
N	1178	1178	1178	578	600
Pseudo-R^2	0.011	0.045	0.052	0.033	0.0003

*Significance codes: 0.001*** 0.01** 0.*

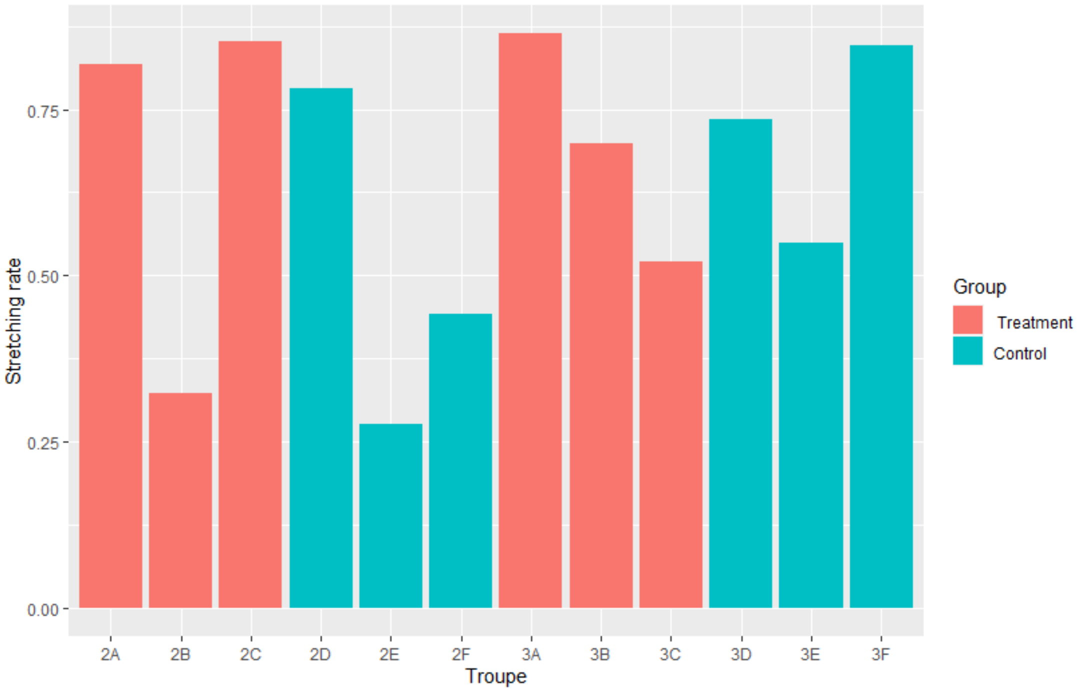
Figure 1: Probability to stretch for age categories



Then, taking into account that age category has a significant effect on probability to stretch, we again estimate model 2 with dataset restricted only either to young or to old category (Table 7, col. 4 and 5). The result is not statistically significant for any of the groups. For category young average marginal effect of treatment is 20.4% but the p-value equals 0.253. For category old the probability to stretch is similar for both groups (p-value = 0.611).

Finally, probability to stretch is assessed for every troupe separately. Figure 2 gives a summary of probabilities to stretch. The results correspond with those examined before. The differences among the troupes are substantial. We can assume that approach of teachers or other characteristics specific to each troupe play an important role. Troupes that belong to the treatment group have on average higher probability to stretch. In addition, troupes from category old have higher probability to stretch compared to those from category young.

Figure 2: Probability to stretch for troupes



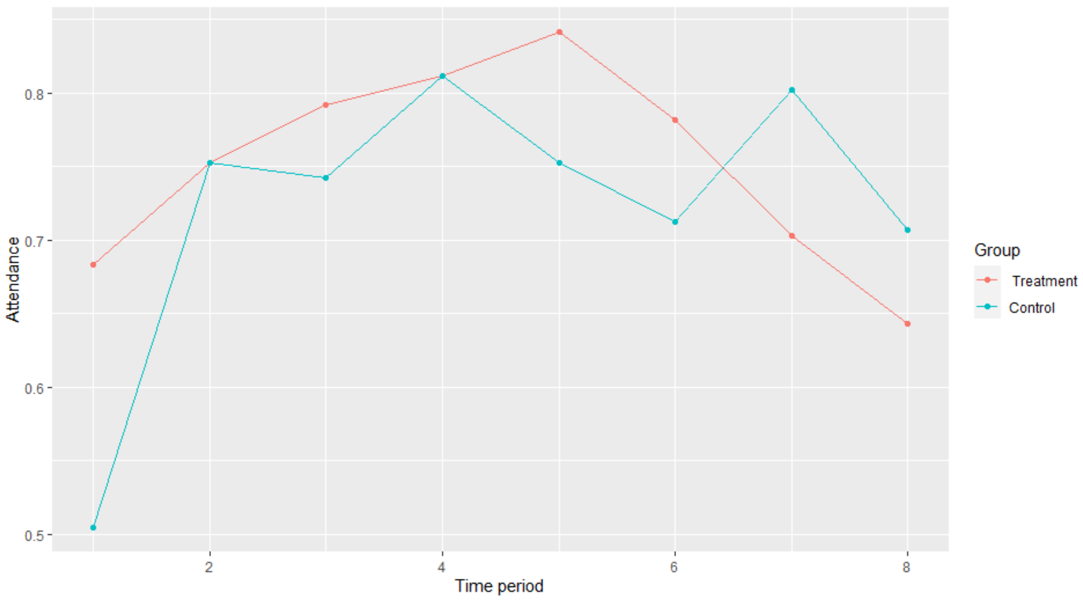
Troupes labeled with number 2 belong to category young, those labeled with number 3 to category old.

7.2.3 Attendance Rate

We want to verify that the attendance rate did not differ for the two groups. If this assumption is not rejected, we expect that the effect of the treatment is not caused by higher attendance of participants in the treatment group or their higher motivation to attend classes.

Difference in attendance rate, defined as proportion of participants attending a class and of those enrolled in a class, was not statistically significant for the groups (p-value = 0.232). On average, attendance rate attained values around 72-75% (Table 2). Figure 3 displays attendance rates for the two groups. On average, young and old category of participants attended classes with the same rate (p-value = 0.494).

Figure 3: Attendance rates for different periods



Moreover, participants attended classes with similar frequency in both groups, as shown in Table 8. Wilcoxon test comparing quantity of participants attending classes for a given number of times returns p-value of 0.725. If we assume that those who attend classes more frequently are more motivated, uneven distribution might cause differences in motivation of participants among the groups. This could further impact motivation to stretch after class.

Table 8: Number of participants who attended classes for a given number of times

Number of attendances	1	2	3	4	5	6	7	8
Treatment group	1	2	5	9	15	22	32	15
Control group	0	5	7	18	12	18	28	13

7.3 Persistence of the Effects of the Treatment

In this part, we estimate the persistence of the treatment effect in time. Figure 4 presents how stretching rate evolved in time for the groups. After first class there was a drop and then, the rate decreased gradually. For the treatment group, the rate rose slightly at the end of the experiment. Specific values of the stretching rate are shown in Table 9. The rate ranges between 46.6% and 92.8%. It is higher for the treatment group. The only exception to this is period 5 when the stretching rate was higher for the control group. Using Wilcoxon test, the treatment effect is statistically significant at 5% level only for periods 2, 4 and 8.

Figure 4: Stretching rate in time

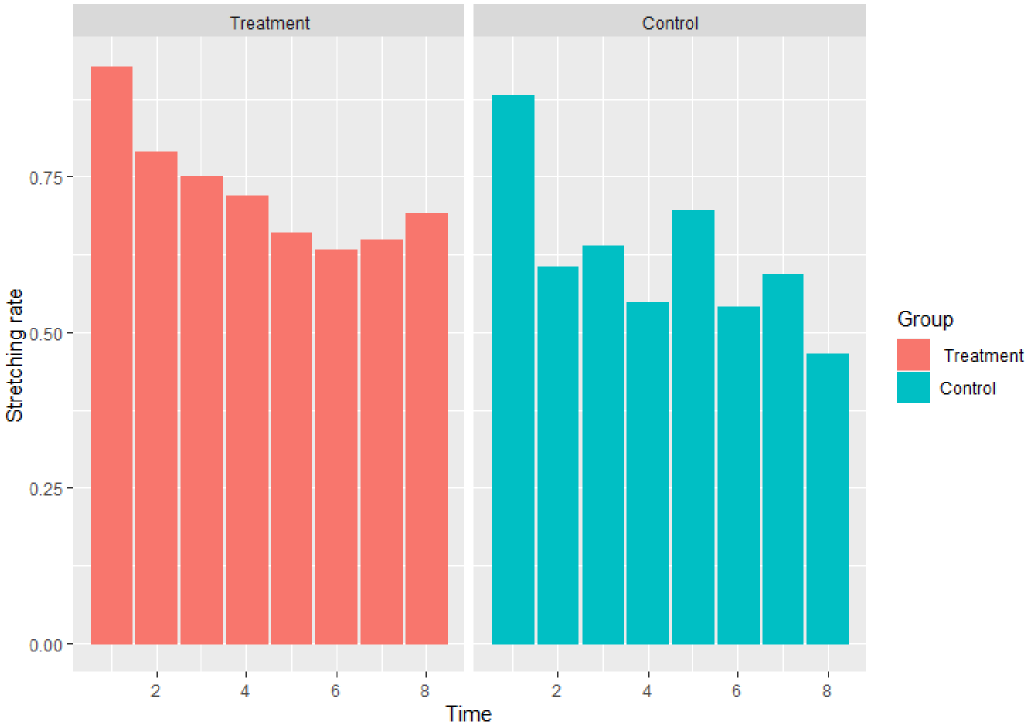


Table 9: Mean values of probability to stretch for different periods

Dependent variable:								
Stretch								
Period	1	2	3	4	5	6	7	8
Mean treatment	0.928	0.790	0.750	0.720	0.659	0.633	0.648	0.692
Mean control	0.882	0.605	0.640	0.549	0.697	0.542	0.593	0.466
Diff in mean	0.046	**0.185**	0.11	**0.171**	-0.038	0.091	0.055	**0.226**
P-value	0.401	**0.014**	0.138	**0.024**	0.604	0.257	0.487	**0.011**
N	120	152	155	164	161	151	152	123

Probit models (Tables 10 and 11) provide corresponding results. The treatment effect is statistically significant for periods 2, 4 and 8. On the other hand, age category has significant effect on probability to stretch in all periods except for periods 1 and 5. When tested for every period separately, the effect of age category is more statistically significant than the effect of treatment.

Table 10: Effect of the treatment for different periods

Dependent variable: Stretch								
Period	1	2	3	4	5	6	7	8
(Intercept)	0.187***	0.267	0.359*	0.123	0.517***	0.105	0.234	-0.087
	(0.229)	(0.146)	(0.148)	(0.139)	(0.151)	(0.148)	(0.147)	(0.165)
Treat	0.271	**0.538***	0.316	**0.459***	-0.108	0.235	0.145	**0.589***
	(0.322)	(0.218)	(0.213)	(0.202)	(0.206)	(0.207)	(0.208)	(0.232)
N	120	152	155	164	161	151	152	123
Pseudo-R^2	0.010	0.033	0.012	0.024	0.001	0.006	0.002	0.039

*Significance codes: 0.001*** 0.01** 0.05*.*

Table 11: Effect of treatment and age category for different periods

Dependent variable: Stretch								
Period	1	2	3	4	5	6	7	8
(Intercept)	0.887**	-0.071	-0.024	-0.141	0.404*	-0.161	0.005	-0.379*
	(0.277)	(0.182)	(0.193)	(0.177)	(0.187)	(0.176)	(0.178)	(0.191)
Treat	0.335	**0.577***	0.374	**0.492***	-0.109	0.198	0.162	**0.519***
	(0.333)	(0.224)	(0.219)	(0.206)	(0.207)	(0.210)	(0.210)	(0.238)
Age0	0.626	**0.698****	**0.693****	**0.498***	0.216	**0.612****	**0.451***	**0.807****
	(0.346)	(0.224)	(0.219)	(0.205)	(0.206)	(0.211)	(0.209)	(0.246)
N	120	152	155	164	161	151	152	123
Pseudo-R^2	0.057	0.086	0.066	0.052	0.007	0.048	0.026	0.106

*Significance codes: 0.001*** 0.01** 0.05*.*

To further estimate long term effects of choice defaults, variable time is added to the model (Table 12, col. 1). It is statistically significant for all the periods. In other words, probability to stretch is lower for all the periods when compared with period 1. This model is preferred by likelihood ratio test to more restricted model 3. Probability to stretch decreased over time, it was the lowest in period 6. When the first period is compared with the last one, probability to stretch decreased on average by 30.2 percentage points (Table 13, col. 1).

The model is also estimated using variable time as a numeric (Table 12, col. 2). On average, probability to stretch decreases in every period by 3.1 percentage points. This result is statistically significant, associated p-value is 0.003. However, this model takes into consideration only linear evolution of probability to stretch in time.

Further, we assessed whether the evolution in time is similar for the treatment and the control group and for age categories. Nonetheless none of the interaction coefficients was statistically significant and therefore, the evolution in time is comparable for the groups (Table 12, col. 3 and 4).

Table 12: Long term effect of treatment (pooled data)

Dependent variable: Stretch	(1)	(2)	(3)	(4)
(Intercept)	0.928**	0.451	0.917*	0.903*
	(0.290)	(0.258)	(0.370)	(0.363)
Treat	0.307	0.316	0.327	0.305
	(0.292)	(0.291)	(0.372)	(0.294)
Age0	0.554*	0.543	0.556*	0.622
	(0.282)	(0.278)	(0.281)	(0.318)
Time2	-0.815**		-0.920*	-0.845*
	(0.288)		(0.414)	(0.374)
Time3	-0.850**		-0.867*	-0.890*
	(0.272)		(0.396)	(0.412)
Time4	-1.008**		-1.089*	-0.949
	(0.343)		(0.523)	(0.512)
Time5	-0.919**		-0.685*	-0.718
	(0.309)		(0.335)	(0.431)
Time6	-1.118***		-1.054***	-1.117**
	(0.299)		(0.315)	(0.380)
Time7	-1.041**		-0.965*	-0.968*
	(0.333)		(0.383)	(0.486)
Time8	-1.096***		-1.206*	-1.177**
	(0.301)		(0.477)	(0.422)
Time		-0.092***		
		(0.028)		

	(1)	(2)	(3)	(4)
Treat*Time2			0.239	
			(0.566)	
Treat*Time3			0.034	
			(0.519)	
Treat*Time4			0.170	
			(0.645)	
Treat*Time5			-0.440	
			(0.597)	
Treat*Time6			-0.126	
			(0.597)	
Treat*Time7			-0.161	
			(0.658)	
Treat*Time8			0.211	
			(0.615)	
Age0*Time2				0.056
				(0.558)
Age0*Time3				0.064
				(0.478)
Age0*Time4				-0.139
				(0.607)
Age0*Time5				-0.407
				(0.577)
Age0*Time6				-0.015
				(0.602)
Age0*Time7				-0.165
				(0.609)
Age0*Time8				0.203
				(0.592)
N	1178	1178	1178	1178
Pseudo-R^2	0.077	0.063	0.082	0.080

*Significance codes: 0.001*** 0.01** 0.05*.*

Table 13: Average marginal effect of variables, corresponding with Table 12

Dependent variable: Stretch				
	(1)	(2)	(3)	(4)
Treat	0.102	0.107	0.101	0.101
	(0.094)	(0.095)	(0.094)	(0.095)
Age0	0.188	0.187	0.188	0.189
	(0.099)	(0.101)	(0.099)	(0.101)
Time2	-0.203		-0.202	-0.203
	(0.074)		(0.071)	(0.074)
Time3	-0.215		-0.215	-0.217
	(0.068)		(0.067)	(0.070)
Time4	-0.270		-0.269	-0.269
	(0.095)		(0.091)	(0.097)
Time5	-0.238		-0.234	-0.232
	(0.087)		(0.084)	(0.085)
Time6	-0.310		-0.309	-0.309
	(0.087)		(0.085)	(0.088)
Time7	-0.282		-0.283	-0.280
	(0.096)		(0.095)	(0.098)
Time8	-0.302		-0.304	-0.294
	(0.085)		(0.084)	(0.085)
Time		-0.031		
		(0.010)		

8 Discussion

In this section, we interpret the results and relate them to the existing research. We note limitations of the research as well as suggestions for future research.

8.1 Discussion of the Results

We take into account that the treatment and the control group have on average the same characteristics and that they are also comparable in terms of attendance rate. On the other hand, inconsistency of the two groups might arise from differences among teachers who lead the classes and different environment classes take place in.

Difference of 17.8 percentage points in enrollment rate between the treatment and the control group was statistically significant. Enrollment rate was 99% for the treatment and 81.2% for the control group. The initial default influenced enrollment and since more individuals were enrolled in the treatment group, we might expect more individuals from this group to stretch. The results show that Hypothesis 1 is valid. It also corresponds with research of Johnson and Goldstein (2003) on organ donation effective consent rates and of Madrian and Shea (2001) on 401(k) plan participation rates, whose results differed even more significantly for the two groups. Enrollment rate for the control group was high in our experiment which might be caused by the introduction of the club. In the studies mentioned, no additional information concerning organ donation, or 401(k) plans was given to people.

Stretching rate was higher by 11 percentage points for the treatment group with the rate of 72.5%. Stretching rate for the control group was 61.5%. This result was statistically significant when mean values were compared but not statistically significant in probit models with clustered standard errors. When tested for each period separately, the effect was significant for periods 2, 4 and 8. We observe positive effect of the treatment for all the models, stretching rate is higher for the treatment group even though the results are not always statistically significant. The research is limited by a sample size and the results might be statistically significant for larger sample. We cannot make conclusions about Hypothesis 2. Literature on the treatment effect of choice defaults reports statistically significant results (Arno & Thomas, 2016; Thaler & Sunstein, 2009; Van Gestel et al., 2018; Wagner & Toews, 2018). Exception to this is a study done by Marcano-Olivier et al. (2019) who reported statistically significant result only for higher consumption of fruits and not of vegetables during the intervention period.

Effect of age category on probability to stretch was statistically significant. Probability to stretch was higher by 19.3 percentage points for category old. Hence, we can reject Hypothesis 4. As stated earlier, no literature that would focus specifically on differences in the effects of choice defaults based on age was found. However, it agrees with studies which concluded that nudges have significant effect on children (Marcano-Olivier et al., 2019; Sutter et al., 2015; Zhao et al., 2021). Furthermore, variable Age was transformed from variable Troupe. It is possible that the effect of age was overlapping with an effect of troupes since characteristics specific to each troupe might have outweighed the effect of age. The analysis has shown that results differed substantially among troupes, no matter whether they belonged to the treatment or the control group. Finally, we found no evidence that the treatment has different effect for young and for old participants.

Eventually, stretching rate decreased in time. Probability to stretch estimated by probit model was by 30.2 percentage points lower at the end of the experiment compared to the period 1. In every period, the probability to stretch decreased on average by 3.1 percentage points. No significant difference in evolution in time was observed for groups or age categories. Interestingly, the treatment effect was statistically significant for periods 2, 4 ad 8. Venema et al. (2018) also examined persistence of the treatment effect of choice defaults that require long-term participation and they came to similar conclusions. The results in absolute values are different but that is probably caused by different type of behavior observed.

8.2 Limitations

Several important limitations of the experiment were recognized. First, when internal validity is concerned, the conditions were not identical for all the individuals. We can observe extraneous factors that probably influenced the results. Classes took place at different environment and at different time of the day. However, distribution of time at which classes finished was similar in both groups and both age categories. It differed by 45 minutes on average. Further, classes were taught by different teachers. They were all given the same instructions nonetheless their personalities, approaches to teaching and to leading a class vary. Probably, some of them were more supportive than others and therefore the stretching rate of respective troupes was higher. Next, the results could be explained by different social interactions. Participants were members of 12 distinct troupes and group dynamics could have played an important role in motivating individuals to stretch. Those who were unsure about stretching after exercise might have been affected by few motivated individuals. As a result, for these troupes stretching rate could have been higher compared to a situation when individuals would not interact with each other. Further, since some of the participants were young and they needed to be accompanied to dance classes by parents, they might have not wanted to let their parents wait and for that reason skipped stretching.

Second, measurement error arising from inaccurate data records caused by forgetfulness of teachers and participants probably had an impact on the results. Moreover, subjectivity is to some extent an issue. Maybe, some individuals considered stretching they did as satisfactory while others viewed the same stretching lasting the same amount of time as insufficient and they did not mark that they stretched.

In addition, the experiment was restricted primarily to girls aged 9 – 18 who take dance classes. Therefore, the sample does not represent the whole population and the experiment cannot be generalized. It is externally valid for a population of girls of the respective age. The size of the sample was also limited, with only 202 participants. Experiment done on a larger simple might provide more accurate and significant results.

Finally, one of major limitations of the experiment is the fact that to determine age of participants, age categories were used instead of exact ages. These age categories also slightly overlap. The results could have been more precise in showing the effect of age on stretching rate.

In our study we explored how choice defaults affect probability to stretch, what is persistence of this effect and how age influences the effect. Future research might focus on replicating this research on larger sample that is more representative of the whole population. Furthermore, it could control for more variables, for example personality characteristics of individuals and of teachers, environmental characteristics such as time of a day, gender, and real age.

9 Conclusion

In this thesis we tested the use of choice defaults in stimulating behavior of dancers. We built on nudge theory introduced by Thaler and Sunstein (2009). We aimed to enhance injury prevention which is one of key factors in reducing government expenditures in healthcare and decreasing financial burden for individuals (Eliakim et al., 2020; Hickey et al., 2014; King et al., 2013; Michaud et al., 2011).

Field experiment examined the effect of choice defaults. Participants aged 9-17 were distributed into the treatment and the control group based on dance troupes they are enrolled to. The treatment group was enrolled in after-class stretching club as a default while the control group was not enrolled as a default. For a month we observed whether participants stretched after class or not.

The results revealed higher enrollment rate and stretching rate for the treatment group which is in line with studies on choice defaults. However, difference in the stretching rates was not always statistically significant. It might be due to limited sample size. Moreover, significant differences in the stretching rate were observed for different troupes in both, the treatment, and the control group which might be caused by non-identical conditions. The results might be influenced by different teachers leading a class, different group dynamics and environment. Analysis revealed statistical significance of the effect of age categories on probability to stretch. Nonetheless, no other research focus on this topic and therefore we cannot compare the results. Age categories were created based on troupes and the effect might be affected by it. Finally, stretching rate decreased in time which is in accordance with findings of other authors.

Literature on use of choice defaults encouraging stretching after exercise is very limited. This thesis contributes to the existing research also in terms of studying persistence of the effect of choice defaults that require long-term participation. It also extends research on choice defaults to children. The results could be used in the healthcare sector as well as among sportsmen.

Future research might focus on extending the sample and making it more representative of the whole population. It could inspect the effect of age more in detail. Finally, other variables could be considered, such as personality characteristics or gender since they might influence the results.

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List of Appendices

Appendix 1

Table A1: Robustness check: Effect of the treatment for pooled data for girls

Dependent variable: Stretch					
				Young category	Old category
	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.287	0.008	-0.112	-0.112	0.699***
	(0.247)	(0.245)	(0.264)	(0.264)	(0.140)
Treat	0.324	0.332	0.575	0.575	0.063
	(0.341)	(0.289)	(0.464)	(0.464)	(0.262)
Age0		0.561*	0.810**		
		(0.277)	(0.299)		
Age0*Treat			-0.512		
			(0.533)		
AME Treat	0.116	0.114	0.115	0.217	0.019
	(0.120)	(0.096)	(0.087)	(0.158)	(0.079)
AME Age0		0.198	0.199		
		(0.103)	(0.095)		
N	1139	1139	1139	550	589
Pseudo-R^2	0.012	0.048	0.055	0.037	0.0005

*Significance codes: 0.001*** 0.01** 0.05*.*