

**Should Individuals Choose
Their Own Incentives?
Evidence from a Mindfulness
Meditation Intervention**

*Andrej Woerner, Giorgia Romagnoli, Birgit M. Probst, Nina Bartmann,
Jonathan N. Cloughesy, Jan Willem Lindemans*

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Poschingerstr. 5, 81679 Munich, Germany

Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de

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Should Individuals Choose Their Own Incentives? Evidence from a Mindfulness Meditation Intervention

Abstract

This paper theoretically and empirically investigates the effects of letting people choose from a menu of increasingly challenging incentive schemes. We derive the conditions under which a policy maker profits from leaving the choice to the individuals by leveraging their private information about the expected benefits from the targeted behavior. We test the theoretical predictions in a field experiment in which we pay participants monetary rewards for completing daily meditation sessions. We randomly assign some participants to one of two incentive schemes and allow others to choose between the two schemes. As predicted, participants sort into schemes in (partial) agreement with the objectives of the policy maker. In contrast to our theoretical predictions, participants who could choose complete significantly fewer meditation sessions than participants that were randomly assigned. Since the results are not driven by poor selection, we infer that letting people choose between incentive schemes may bring in psychological effects that discourage adherence.

JEL-Codes: C900, D030, D800, I100.

Keywords: monetary incentives, dynamic incentives, field experiment, mental health.

*Andrej Woerner**
LMU Munich / Germany
andrej.woerner@econ.lmu.de

Birgit M. Probst
TU Munich / Germany
birgit.probst@tum.de

Jonathan N. Cloughesy
Duke University / Durham / NC / USA
jonathan.cloughesy@duke.edu

Giorgia Romagnoli
University of Amsterdam / The Netherlands
g.romagnoli@uva.nl

Nina Bartmann
Duke University / Durham / NC / USA
nina.bartmann@duke.edu

Jan Willem Lindemans
Duke University / Durham / NC / USA
jan.lindemans@duke.edu

*corresponding author

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1 Introduction

Monetary incentives have proven to help individuals lead healthier lifestyles.¹ Traditionally, policy makers have offered a single incentive scheme to their population of interest. However, one size may not fit all when individuals are heterogeneous with respect to the perceived benefits and costs involved in adhering to the incentivized behavior. Consider an incentive scheme that pays a low reward for reaching an easy target compared to one that pays a high reward for reaching a difficult target. The first scheme may be better suited at boosting adherence for individuals with a low benefit-cost ratio, as they would find the second scheme too challenging. Conversely, individuals with a high benefit-cost ratio would likely be better incentivized by the second scheme, as they might reach the easy target even in the absence of incentives.

In a heterogeneous population, a policy maker may want to offer different incentives to different individuals. However, informational asymmetries are likely to be in place: While individuals often have a good understanding about their own preferences, the policy maker rarely knows individuals' types. Crucially, well-designed monetary incentives can create a partial alignment of interests in that both the policy maker and individuals benefit from higher adherence. Thus the question arises as to whether the policy maker can extract individuals' private information by letting them choose between several incentive schemes.²

In this paper, we study whether giving people the choice between incentive schemes that are ranked in terms of how challenging and rewarding they are increases adherence compared to the traditional approach of exogenously assigning incentives. Our paper combines theoretical analysis and empirical results. More specifically, we derive a model that highlights the conditions under which letting individuals choose between incentive schemes can lead to higher adherence. We then test our theoretical predictions with a field experiment on mindfulness meditation.³

¹See e.g. [Charness and Gneezy, 2009](#); [Giné et al., 2010](#); [Royer et al., 2015](#); [Augurzky et al., 2018](#); [Schilbach, 2019](#); [Carrera et al., 2020](#); [Brownback et al., 2021](#); [Aggarwal et al., 2020](#).

²Next to extracting private information, choice might also increase adherence due to agency or psychological ownership effects ([Bartling et al., 2014](#); [Fehr et al., 2013](#); [Dawkins et al., 2017](#)).

³Mindfulness meditation is a mental health practice that involves a present-moment orientation and trains an accepting attitude towards one's experience. [Cassar et al. \(2020\)](#) and [Charness et al. \(2021\)](#) find a positive effect for a mindfulness meditation program on incentivized cognitive tasks as well as self-reported measures of mental well-being. Recent meta-analyses further suggest that mindfulness-based interventions can improve outcomes related to stress, depression and anxiety, insomnia, chronic pain, smoking cessation, weight loss, and other clinically relevant outcomes ([Goyal et al., 2014](#); [Khoury et al.,](#)

Theoretically, we study a setting populated by agents which are heterogeneous in the benefits they derive from meditating and model a policy maker whose intention it is to increase the average frequency of meditation sessions. We postulate that the policy maker can choose between two incentive schemes. The first is a low-challenge-low-reward scheme that pays agents a constant monetary reward for each completed meditation session. We call this the Constant scheme. The alternative is a Streak scheme, a high-challenge-high-reward scheme that pays agents a larger per-session reward conditional on the successful completion of a prespecified number of consecutive meditation sessions. Our model easily generalizes to settings characterized by a set of incentive schemes that can be ranked based on how challenging and rewarding they are. The key ingredient is a single-crossing property such that the low-challenge-low-reward scheme rewards relatively more for low completion rates while the high-challenge-high-reward scheme rewards relatively more for high completion rates.⁴ We first show that these two schemes are both predicted to raise meditation frequencies compared to a baseline where no monetary incentives are given. We further show that, from the perspective of the policy maker, the first-best allocation of these two schemes follows a threshold strategy where the less challenging Constant scheme is assigned to individuals with low benefits from meditation, and the Streak scheme is assigned to individuals with high benefits.

We assume that the policy maker suffers from asymmetric information in that individuals' meditation benefits are private knowledge.⁵ In this context, we study the opportunity to let the agents choose between the two incentive schemes. We prove that, when given the choice, individuals sort in the two schemes in partial accordance with the intentions of the policy maker: High-benefit individuals choose the Streak scheme and low-benefit individuals choose the Constant scheme. This sorting allows the policy maker to capitalize

2015; Gong et al., 2016; Carrière et al., 2018; Goldberg et al., 2018; Heckenberg et al., 2018; Reangsing et al., 2020; Scott-Sheldon et al., 2020; Wang et al., 2020).

⁴In this study, we focus on Constant and Streak incentive schemes. Constant incentives are arguably the simplest and most utilized form of incentives, and thus extensively studied. We combine the Constant scheme with a Streak incentive scheme for two reasons. First, Streak schemes provide extra monetary incentives in every period. In contrast, alternative dynamic schemes such as threshold incentive schemes, in which individuals are only monetarily rewarded if they accomplish a predefined frequency target, do not offer further extra incentives when the threshold is out of reach or already met. Second, streaks are also often used to motivate people in practice, in particular on popular mobile applications, such as Duolingo or Snapchat. For example, the "Snapstreaks"-feature on Snapchat keeps track of how many days in a row one has kept the conversation going and rewards the user with different emojis depending on the number of days.

⁵Alternatively, the policy maker may know the individual type, but it may be politically unfeasible to exogenously assign different schemes to different individuals.

on the information owned privately by the individuals.

However, there is generally a discrepancy between the threshold chosen by the individuals and the one that the policy maker would optimally set: Too many individuals select into the easier Constant scheme than would be socially desirable. In fact, the sub-optimal threshold that follows a free choice of schemes can, under certain conditions, backfire and lead to lower frequencies than the exogenous allocation. To tackle this issue, we formally highlight specific and actionable conditions that ensure that letting agents choose their incentive scheme performs better than a traditional exogenous allocation of incentives. One sufficient condition is that the Constant scheme leads to a weakly higher average expected meditation frequency than the Streak incentive scheme. This is an easily verifiable condition if the policy maker has historical data available regarding the performance of pre-existing schemes in a comparable population of subjects. The second sufficient condition (which is the one we exploit in our field experiment), is that the proportions of agents assigned to the Constant scheme is at least as high as the proportion of agents self-selecting into the Constant scheme. In two theoretical extensions in the appendix, we show that our results carry over to when the policy maker aims to maximize welfare rather than meditation frequency, as well as when agents are present-biased as long as benefits and present bias are independent from each other.

We then test the predictions of our model with a field experiment on mindfulness meditation. A meditation setting is particularly suitable to study the effect of letting people choose their incentive schemes for the following three reasons. First, our field experiment on meditation provides estimates about the effect of choice in an important health-related and real-life application. Second, there is a high heterogeneity in the benefits people derive from meditating, which is required in order for one incentive scheme to work better for some and another scheme for others. And third, as pre-intervention meditation frequency is (almost) impossible to verify, it is difficult for a policy maker to accurately identify people's types. This implies that the policy maker has to rely on people's self-selection if she wants to improve on a random allocation to incentive schemes. Beyond the effect of choice, a meditation intervention also allows us to study whether monetary incentives are not only an effective way to change people's behavior in the physical health domain, but whether they also work for an activity related to mental health.

We conducted our experiment with 499 students at the University of Amsterdam. Stu-

dents were invited to participate in a 36-day mindfulness meditation program consisting of short, daily online meditation sessions. We randomize subjects into three treatments: *Control*, *Random* and *Choice*. In all three treatments, subjects receive access to meditation audio files. Subjects in *Random* and *Choice* are additionally paid for completing meditation sessions. In *Random*, subjects are randomly allocated to either a Constant or Streak incentive scheme. In *Choice*, subjects can choose between the Constant and Streak incentive scheme. The Constant scheme pays subjects €2 for each day that they successfully complete that day’s meditation session. The Streak scheme pays subjects €8 for each series of three days in which they consecutively complete the day’s meditation session.⁶

Our results partially align with our model’s predictions. As expected, both the Constant and Streak incentive scheme significantly increase average meditation frequency compared to the control group, and do so almost to the same extent. Further, subjects with high perceived meditation benefits meditate more when randomly assigned to the Streak incentive scheme, and subjects with low benefits meditate more when randomly assigned to the Constant incentive scheme. We also find that subjects in *Choice* partially separate in accordance with their expected meditation frequency. Contrary to our theoretical predictions, however, our data show that subjects who were allowed to choose their incentive scheme meditate significantly *less* than subjects who were randomly assigned. This surprising effect is entirely driven by subjects who did not meditate at baseline. Ruling out poor selection as a potential explanation for the negative effect of *Choice*, we infer that the negative effect of letting people choose their own incentives must come from the act of choosing itself. We then suggestively highlight potential psychological channels through which this can happen. We provide some support for a demotivating effect via self-signaling, and find no evidence in favor of other potential explanations, namely regret aversion, differences in presentation or dislike of choice.

Our paper thus shows that monetary incentives are a viable tool to substantially increase meditation frequency. While our theory predicts that choice should increase adherence, our experimental results show that letting people choose might actually backfire.

The remainder of the paper is structured as follows. The following section discusses

⁶We used a 3-day streak to make the Streak scheme notably different from the Constant scheme, while trying to ensure that participants stayed motivated enough to start a new streak if they failed to complete their current streak.

the related literature. Section 2 provides theoretical predictions for the experimental results. Section 3 presents the experimental design. Section 4 shows and discusses the experimental results. Section 5 investigates potential explanations for the negative net effect of *Choice* on meditation frequency. Finally, Section 6 concludes.

1.1 Contribution to the Literature

Our paper contributes to three strands of the literature. First, we contribute to the literature investigating how monetary incentives can be used to promote healthy behaviors. Researchers and policy makers have evaluated the effects of monetary incentives to induce behavioral change related to health in various areas such as physical activity, weight loss and smoking (see e.g. [Volpp et al., 2008](#); [Charness and Gneezy, 2009](#); [Giné et al., 2010](#); [Halpern et al., 2015](#); [Augurzky et al., 2018](#); [Aggarwal et al., 2020](#); [Milkman et al., 2021](#)). The main finding is that such monetary incentives are overall effective in pushing individuals towards healthy actions. The literature also finds that healthy behavior continues right after the end of the intervention, but that the positive behavioral effects decay within a couple of weeks or months ([Charness and Gneezy, 2009](#); [Acland and Levy, 2015](#) ([März, 2019](#)); [Royer et al., 2015](#)). We contribute to this literature by showing that monetary incentives can also be used to change people’s behavior in the domain of mental health.⁷ Our paper suggests that one can view monetary incentives for physical and mental health as conceptually similar. In our study, we confirm the general finding that monetary incentives can effectively increase adherence during the intervention period but that there are no long-term effects.

Second, we contribute to the small but growing literature on designing more effective subsidy schemes for behavioral change. Recent papers have investigated how the overall effectiveness of incentives depends on their timing and structure. With respect to timing, constant incentives over time seem to be more effective than exogenously increasing and decreasing incentives ([Bachireddy et al., 2019](#); [Carrera et al., 2020](#)). With respect to structure, [Aggarwal et al. \(2020\)](#) theoretically and experimentally show that threshold incentives are a viable alternative to constant incentives. In their experiment, they find that threshold incentives are more cost-effective but lead to higher dispersion in outcomes than constant incentives. Our paper is the first to investigate another type of dynamic

⁷To our knowledge, we are the first to study monetary incentives in the mental health domain.

incentives for behavioral change, streak incentives.

Third, we contribute to the literature on the effects of letting people choose their own monetary incentives. The majority of these studies have investigated settings in which individuals have to decide whether they want to take-up an incentive scheme with which they might lose money. Such monetary bets and commitment contracts can help individuals overcome their time-inconsistency problems. As many people are unwilling to put their own money at risk, empirical studies on bets and ‘pure’ commitment contracts typically find relatively low take-up rates, which mitigate overall effects (Halpern et al., 2015; Giné et al., 2010; Royer et al., 2015; John, 2020; Adjerid et al. (2021); Woerner, 2021).⁸ A second finding of this literature is that it is difficult to predict who takes up a bet or commitment contract (Giné et al., 2010; Carrera et al., Forthcoming). Our results show that it is also difficult to predict which subsidy schemes individuals choose.⁹

Our paper is among only a few studies that investigate the effects of letting people choose *between* incentive schemes. Babcock et al. (2015) have participants choose between individual and team incentives for study room usage. They find that almost all participants prefer the individual incentive over the team incentive even though team incentives are more effective. They also find that participants who were allowed to choose have a higher attendance than participants who were exogenously assigned to the individual incentive. Put together, their result suggests that the pure act of choosing (net of selection effects) increases adherence. In contrast, our experimental results show that letting people choose can also decrease adherence.

In the context of walking, Adjerid et al. (2021) let participants choose between a constant pay rate and a higher-sized bet. The paper compares individuals that are assigned to their preferred scheme with individuals that are randomly assigned to either scheme. Differently from our study, this paper studies a case in which the policy maker has a clear preference for the bet scheme, but because she cannot force participants to take up a bet (where money can be lost), she lets them choose. Another difference is that,

⁸Take-up rates are higher if participants cannot lose their own money but instead merely lose their experiment earnings (see Carrera et al. (Forthcoming) for an overview of take-up rates in commitment contract studies).

⁹The difficulty in predicting individual preferences for incentive schemes seems to be a general problem. In a lab experiment with hypothetical choices, Lipman (2020) lets participants tailor their own incentive schemes along several dimensions. While there is quite some heterogeneity in participants’ preferred incentive schemes, Lipman finds no association between participants’ selected tailored incentives and economic preferences.

seen through the lens of our model, their setting is one where self-selection into schemes is orthogonal to the objectives of the policy maker.¹⁰ In practice, the authors even find evidence for unfavorable selection, in that it is exactly the participants who choose the constant pay rate who would have walked considerably more with the bet scheme. Our paper investigates a case in which there is predicted and observed positive (partial) alignment between the policy maker’s preferences and individuals’ incentive scheme choices. While we also find a negative effect of letting individuals choose, this effect is not driven by unfavorable selection, but rather by psychological effects. This paper thus provides evidence that letting individuals choose between incentive schemes might backfire even if the menu of incentive schemes is designed to ensure aligned interests of the policy maker and individuals.

Our paper is most closely related to [Dizon-Ross and Zucker \(2021\)](#) who test the effectiveness of letting people choose between three threshold-incentive schemes with increasing difficulty and earnings potential. Similar to [Adjerid et al. \(2021\)](#), they conduct a field experiment on walking. In contrast to their and our findings, however, [Dizon-Ross and Zucker \(2021\)](#) find a positive effect of letting people choose. Participants who could choose between incentives had a significantly higher increase in daily steps than participants that were exogenously assigned to the medium threshold. Our paper provides evidence of the opposite; in our experiment, participants who choose their incentive scheme meditate less than participants who are randomly assigned. A potential explanation for this discrepancy is experience with the targeted behavior. In our experiment, the negative effect of *Choice* compared to *Random* is entirely driven by the 80% of participants who did not meditate at baseline and therefore have likely little experience with meditation in general. As [Dizon-Ross and Zucker \(2021\)](#) incentivize walking, they study an activity which arguably all their participants have quite some experience with. Put together, prior experience could thus explain the two contrasting findings.

Our paper also relates to the contract theory literature with intrinsically motivated agents (cf. [Murdock, 2002](#); [Besley and Ghatak, 2005](#)). Similar to this literature, our model assumes that agents do not only care about financial rewards but also derive intrinsic benefits from the targeted behavior. In contrast to this literature, however, the policy

¹⁰The bet scheme is expected to increase adherence by a constant rate across the participants’ type space (both compared to the constant pay rate and to the no-incentives baseline); this means there are no expected benefits in terms of increased adherence coming from letting participants self-select instead of operating a quota-preserving random assignment.

maker in our model is interested in the frequency of the targeted behavior resp. welfare rather than profit. Finally, as we let participants choose between incentive schemes that are clearly ranked in terms of how challenging they are, participants are pushed towards thinking about their meditation frequency goals, which relates our paper to the literature on goal setting (cf. [Corgnet et al., 2015](#); [Koch and Nafziger, 2020](#); [van Lent and Souverijn, 2020](#)).

2 Theory

We introduce a simple model to show under which conditions the policy maker can alleviate informational asymmetry problems by letting people choose between incentive schemes. Furthermore, we derive theoretical predictions that we then test in our field experiment.

2.1 Model

The target population is described as a continuum of rational, selfish and risk-neutral agents. Agents differ only in their perceived benefits from meditating. Every agent i knows her own benefits type b_i . This information is private knowledge. The distribution of types is $G(b_i)$ with $G(b_{min}) = 0$ and $G(b_{max}) = 1$. In each time period $t \in \{1, 2, \dots, \infty\}$, agents first learn about their period-specific opportunity costs of meditating.¹¹ These costs are i.i.d. and drawn from a standard uniform distribution $c_{it} \sim U[0, 1]$. In every period, agents first observe their cost draw and then take a binary decision whether to meditate or not. If the agent meditates in period t , she obtains deterministic health benefits $b_i > 0$ but incurs the period's costs c_{it} . Moreover, when an agent meditates, she exerts positive externalities $e > 0$ on the policy maker.¹² If an agent does not meditate, she obtains no benefits and incurs no costs, and also produces no positive externalities.

Agents do not take the positive externality of meditating into account. Because of this, a policy maker can increase welfare by monetarily incentivizing agents to meditate more. The policy maker can choose from a finite set of incentive schemes which are ordered in

¹¹Even though our experiment only lasts 36 days, our model assumes an infinite number of periods for reasons of tractability. Simulations results with 36 periods are virtually identical to our analytical results with an infinite number of periods.

¹²Positive externalities of meditating could, for example, stem from reduced public health expenditures or increased work productivity ([Lomas et al., 2017](#); [Duarte et al., 2019](#)).

terms of the challenge they present and the monetary rewards they entail. To ease the exposition, we assume here that the policy maker has the following two incentive schemes at his disposal:

Constant incentive scheme. With a Constant incentive scheme, an agent obtains a constant monetary reward $m_c > 0$ for every period in which she meditates.

Streak incentive scheme. With a Streak incentive scheme, an agent obtains a monetary reward $m_s > 0$ every time she meditates in two consecutive periods. Once the agent has completed a streak, the count is set back to zero.¹³

The policy maker can decide whether to assign each agent to one of the two incentive schemes or to let agents choose between the two incentive schemes. To make the policy maker’s decision non-trivial, we impose that not all types meditate more under the Constant or Streak scheme. We further assume that $\max\{m_c, m_s\} + b_{max} < 1$ to simplify the analysis. This condition ensures that there is no period in which an agent always meditates under the Constant or Streak incentive scheme.

Before turning to the analysis, we want to highlight that the subsequent results are robust to changes in our model. Recall that, in order to allow for a tractable analysis, we make several simplifying assumptions about agents’ preferences, namely rationality (and thus time consistency), selfishness, risk neutrality and independent cost draws. Relaxing these assumptions would alter the relative performance and attractiveness of the Constant and Streak incentive scheme. For example, risk-averse agents meditate comparatively less under the more risky Streak scheme than risk-neutral agents. In contrast, the Streak scheme obviously works comparatively better when there is some form of positive interdependency within consecutive periods, e.g. via agents having regular schedules or forming meditation habits. Crucially, however, as long as these alterations are not systematically correlated with agents’ meditation benefits, they do not change the comparative statics and thus will not affect our subsequent main results about the effect of choice. Appendix C shows that the same results obtain with an alternative model with present-biased, and thus time-inconsistent, agents.

¹³For simplicity, we analyze the 2-period streak rather than the 3-period streak that we implement in the experiment. Simulation results suggest that the comparative statics are not altered by using the simpler 2-period version.

2.2 Analysis

We now analyze the outcomes of exogenously assigning agents to either one of the two schemes and the effect of letting agents choose. We compare these to each other and to the baseline where no incentives are offered.

2.2.1 Baseline

In the baseline, agent i meditates in period t if and only if $b_i \geq c_{it}$ and thereby obtains a utility of $U_i^B = \max\{b_i - c_{it}, 0\}$. In period 0, the agent has not yet learned the realizations of $c_{it} \forall t$, so that her expected meditation frequency is $\mathbb{E}[F_i^B] = b_i$. Her expected per-period utility equals

$$\mathbb{E}[U_i^B] = \int_0^{b_i} (b_i - c_{it}) dc_{it} = \frac{1}{2} b_i^2. \quad (1)$$

An agent's expected meditation frequency and utility thus increase in her meditation benefits. Note that agents meditate inefficiently whenever her costs are higher than her benefits but lower than her benefits plus the externality, thus if $b_i + e > c_{it} > b_i$. This inefficiency is the reason why a benevolent policy maker might intervene and offer agents incentives to increase their meditation frequency.

2.2.2 Exogenous incentives

We modify the baseline setting to accommodate monetary incentives for meditating. We assume utility is additive in this monetary component.

Constant incentive scheme. In this scheme, the agent receives a constant reward m_c for each period in which she completes a meditation session. Thus, agent i meditates in period t if and only if $b_i + m_c \geq c_{it}$. She thereby obtains per-period utility $U_{it}^C = \max\{b_i + m_c - c_{it}, 0\}$. Her expected meditation frequency is thus $\mathbb{E}[F_i^C] = b_i + m_c$ and her expected per-period utility equals

$$\mathbb{E}[U_i^C] = \int_0^{b_i + m_c} (b_i + m_c - c_{it}) dc_{it} = \frac{1}{2} (b_i + m_c)^2. \quad (2)$$

Clearly, an agent's expected meditation frequency and utility increase in her benefits and the constant reward.

Streak incentive scheme. The analysis of the Streak incentive scheme is more com-

plicated. An agent's behavior in a first streak-period, i.e. the first period of a 2-period streak, depends on her beliefs about behavior in second streak-periods. In contrast, an agent's behavior in second streak-periods does not depend on beliefs. This is because the period following a second streak-period is always a first streak-period irrespective of whether the agent meditates or not. We thus start solving the problem for second streak-periods. Here, an agent faces the same decision problem as with a constant incentive scheme, except that the extra reward for meditating in this period equals m_s instead of m_c . Agent i thus meditates in second streak-periods if and only if $b_i + m_s \geq c_{it}$. This yields an expected meditation frequency in second streak-periods of $\mathbb{E}[F_i^{S2}] = b_i + m_s$ and an expected per-second-streak-period utility of $\mathbb{E}[U_i^{S2}] = \frac{1}{2}(b_i + m_s)^2$. First streak-periods do not directly generate a monetary reward for meditating. Meditating in such periods merely preserves the chance to receive m_s in the subsequent period. If the agent does not meditate, she foregoes this chance and anew enters a first streak-period. Denote the value that agent i assigns to keeping the chance to obtain m_s in the subsequent period by option value v_i . Agent i thus meditates in first streak-periods if and only if $b_i + v_i \geq c_{it}$. Therefore, her expected meditation frequency in first streak-periods is $\mathbb{E}[F_i^{S1}] = b_i + v_i$ and her expected per-first-streak-period utility equals $\mathbb{E}[U_i^{S1}] = \int_0^{b_i+v_i} (b_i - c_{it}) dc_{it} = \frac{1}{2}(b_i^2 - v_i^2)$. Note that the agent thus obtains expected negative utility in first streak-periods if $v_i > b_i$. In such cases, the agent is willing to suffer a utility loss in first streak-periods to increase her chance to receive m_s in second streak-periods.

Denote as q_i (resp. $1 - q_i$) the likelihood of the agent being in a first (resp. second) streak-period. The agent's overall expected per-period utility $\mathbb{E}[U_i^S] = q_i \mathbb{E}[U_i^{S1}] + (1 - q_i) \mathbb{E}[U_i^{S2}] = \frac{q_i}{2}(b_i^2 - v_i^2) + \frac{1-q_i}{2}(b_i + m_s)^2$ is a weighted average of her expected per-period utilities in first and second streak-periods. Now, note that agents only enter a second streak-period in period t if they were in a first streak-period in $t - 1$ and also meditated in $t - 1$. Therefore, the likelihood of an agent being in a second streak-period equals the likelihood of the agent being in a first streak-period times her expected meditation frequency in first streak-periods. Formally, this implies that $(1 - q_i) = q_i(b_i + v_i)$ must hold, which simplifies to $q_i = \frac{1}{1+b_i+v_i}$. Inserting q_i into $\mathbb{E}[U_i^S]$ and maximizing w.r.t. option value v_i yields an agent's overall expected per-period utility

$$\mathbb{E}[U_i^S] = \frac{1}{2} \left(\sqrt{(1 + b_i + m_s)^2 - 2m_s} - 1 \right)^2 = \frac{1}{2} (b_i + v_i^*)^2 \quad (3)$$

where $v_i^* = \mathbb{E}[U_i^{S^2}] - \mathbb{E}[U_i^S] = \sqrt{(1+b_i+m_s)^2 - 2m_s} - 1 - b_i$.¹⁴ The resulting expected meditation frequency then equals $\mathbb{E}[F_i^S] = q_i(b_i + v_i^*) + (1 - q_i)(b_i + m_s) = \frac{\sqrt{(1+b_i+m_s)^2 - 2m_s} - 1}{\sqrt{(1+b_i+m_s)^2 - 2m_s}}(1 + b_i + m_s)$.

We are now ready to state the formal results that giving monetary incentives increase agents' expected meditation frequencies and utilities under both schemes compared to the baseline where no incentives are offered.

Proposition 1 (Incentive effect) *Both the Constant and Streak incentive scheme increase an agent's expected meditation frequency and expected utility.*¹⁵

When the monetary incentives are chosen so that no scheme yields an unambiguously higher payoff than the other, the two incentive schemes are naturally ordered in terms of the challenge and the rewards they entail. Compared to the Streak scheme, the Constant incentive scheme is a relatively low-challenge-low-reward scheme. Thus, it stands to reason that the Constant scheme is better calibrated for individuals with low meditation benefits, who find the streak reward too demanding and risky. Conversely, the Streak scheme is better at extracting marginally higher commitment to high meditation frequencies from agents with high benefits. In the next proposition, we formalize this intuition with a single-crossing result. In it, we show that there is a threshold type b^* such that for all types $b_i < b^*$ the Constant scheme performs better (i.e., it improves meditation rates more than the Streak scheme); and, vice versa, for all types $b_i > b^*$ the Streak scheme performs better.¹⁶

Proposition 2 (Single crossing) *There is a threshold type b^* such that for all $b_i > b^*$ (resp. $b_i < b^*$), the expected meditation frequency is larger (resp. lower) under the Streak than under the Constant incentive scheme.*

First-best allocation and random allocation. Based on Proposition 2, we define the *first-best allocation* of agents to schemes as the allocation that maximizes expected meditation frequency in the population as a whole. This allocation assigns all types $b_i < b^*$ to

¹⁴It is easy to see that $m_s > v_i^* = \sqrt{(1+b_i+m_s)^2 - 2m_s} - 1 - b_i$, which implies that, under Streak, agents meditate more frequently in second streak-periods compared to first streak-periods.

¹⁵All proofs are in Appendix A.

¹⁶Throughout the analysis, we use meditation frequency as an easily observable proxy for overall welfare. This link is warranted whenever the positive externality is comparatively large compared to the reward levels, which is a realistic assumption when policy makers are budget-constrained. Appendix B analytically shows that the results for meditation frequency carry over to welfare in our region of interest.

the Constant scheme, and all types $b_i > b^*$ to the Streak scheme. The expected meditation frequency achieved under this policy is $\mathbb{E}[F^{FB}] = \int_{b_{min}}^{b^*} \mathbb{E}[F_i^C]g(b_i)db_i + \int_{b^*}^{b_{max}} \mathbb{E}[F_i^S]g(b_i)db_i$.

Notice that, since the types are private information, the policy maker cannot attain the first-best allocation. Absent this information, the policy maker could allocate these schemes exogenously by randomly assigning a fraction p of individuals to the Constant scheme and a fraction $(1 - p)$ to the Streak scheme. The expected meditation frequency of this *random allocation* is $\mathbb{E}[F^{Ra}] = p \int_{b_{min}}^{b_{max}} \mathbb{E}[F_i^C]g(b_i)db_i + (1 - p) \int_{b_{min}}^{b_{max}} \mathbb{E}[F_i^S]g(b_i)db_i$. Note that the random allocation entails the two corner cases in which the policy maker assigns all agents to the Constant ($p = 1$) resp. Streak incentive scheme ($p = 0$).

2.2.3 Choice

We now study the setting where agents are offered a choice between a Constant and Streak incentive scheme in period 0. Rational agents choose the incentive scheme with the higher expected utility. As $\mathbb{E}[U_i^C] = \frac{1}{2}(b_i + m_c)^2$ (2) and $\mathbb{E}[U_i^S] = \frac{1}{2}(b_i + v_i^*)^2$ (3), an agent thus chooses the Constant incentive scheme if $v_i^* < m_c$, is indifferent if $v_i^* = m_c$, and chooses the Streak incentive scheme if $v_i^* > m_c$. As the likelihood to obtain the reward in a second streak-period is increasing in an agent's baseline frequency, so does the option value v_i^* . This yields the following proposition.

Proposition 3 (Separation) *Denote by $b' = \frac{m_c^2 + 2m_c - m_s^2}{2(m_s - m_c)}$ the type of agent that is indifferent between choosing the Constant and Streak incentive scheme. Then all agents with $b_i < b'$ choose the Constant and all agents with $b_i > b'$ choose the Streak incentive scheme.*

Agents thus separate according to their benefits from meditation. Unsurprisingly, the larger m_s is relative to m_c , the lower becomes b' , and vice versa. If either reward becomes too large in comparison to the other, then $b' < b_{min}$ or $b' > b_{max}$ and all agents select into the more generous incentive scheme. To rule out these trivial cases, we assume that $b_{min} < b' < b_{max}$ for the remainder of the analysis.

Chosen allocation. We define as *chosen allocation* the allocation of agents to schemes that ensues when agents are given the choice between the Constant and Streak incentive scheme. Based on Proposition 3, the average expected meditation frequency of the chosen allocation is $\mathbb{E}[F^{Ch}] = \int_{b_{min}}^{b'} \mathbb{E}[F_i^C]g(b_i)db_i + \int_{b'}^{b_{max}} \mathbb{E}[F_i^S]g(b_i)db_i$.

2.2.4 Choice vs. exogenous incentives

Comparing the random and chosen allocation, it becomes clear that expected meditation frequencies within incentive schemes differ between agents who are offered a choice and who are exogenously assigned to a scheme.

Proposition 4 (Ex-post separation) *Agents who choose the Constant (Streak) incentive scheme have a lower (higher) expected meditation frequency than agents who are randomly assigned to the Constant (Streak) scheme.*

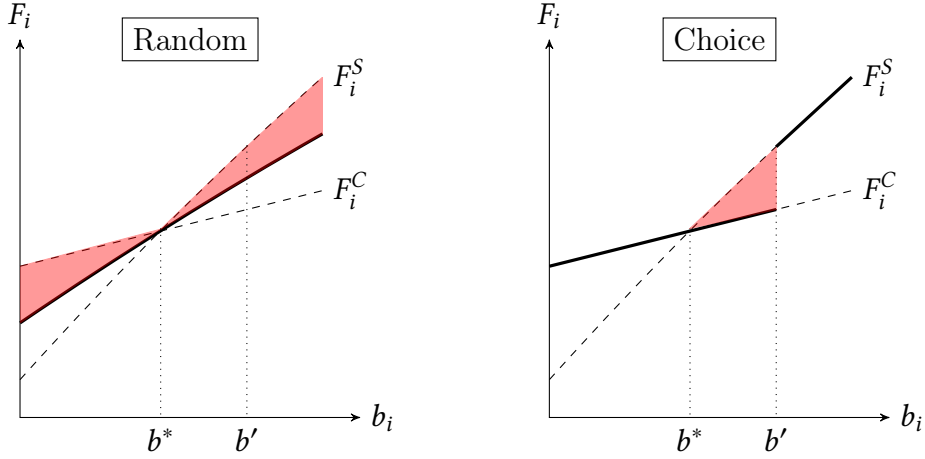
The proposition implies that there is a larger difference between average meditation frequencies in Streak and Constant when agents can choose compared to when they are exogenously assigned to the two schemes.

By giving monetary incentives, the policy maker partially aligns the agents' incentives to his own objectives. Since monetary rewards make agents' utility increase in meditation frequency, it is not surprising that agents sort into meditation schemes in partial accordance with the desired allocation of the policy maker, with high-benefit agents sorting into the Streak scheme and low-benefit agents sorting into the Constant scheme. However, since the policy maker maximizes frequencies while the agents maximize utility, this alignment is only partial and generally there is a wedge between the desired threshold optimally chosen by the policy maker b^* and the actual separating threshold b' chosen by the agents. It is easy to see that $b^* < b'$.¹⁷ As a result of this wedge the meditation frequency achieved by choice is below the first-best allocation.

Figure 1 illustrates the welfare losses (in terms of missed meditation frequencies) associated with, respectively, the random allocation and the chosen allocation, compared to the first-best allocation. The chosen allocation performs better than the random allocation at the extremes of the type distribution where types sort in accordance with the policy maker's objectives. Vice versa, the chosen allocation performs worse than the random allocation in the type range (b^*, b') . Here, all types are misallocated from the perspective of the policy maker in the chosen allocation, while only a fraction p is misallocated in the random allocation.

¹⁷Recall that for type b' it holds that $v_i^* = m_c$. Plugging m_c into $\mathbb{E}[F_i^S(b')]$ yields $\mathbb{E}[F_i^S(b')] = \frac{1+b'+m_c}{1+b'+m_c}(b'+m_c) > b'+m_c = \mathbb{E}[F_i^C(b')]$. As $\frac{\partial[\mathbb{E}[F_i^S]-\mathbb{E}[F_i^C]]}{\partial b_i} > 0 \forall i$, it follows that $b^* < b'$.

Figure 1: Meditation Frequencies



Note: The figure shows average expected meditation frequencies (in bold) depending on type b_i for an example (50%-50%) random allocation (left graph) and the chosen allocation (right graph). The dashed lines depict expected meditation frequencies with the Constant resp. Streak incentive scheme. The red areas picture welfare losses (in terms of missed expected meditation frequencies) compared to the first-best allocation.

Whether the chosen allocation performs better than the random allocation or vice versa depends on the distance between b^* and b' and the type distribution. If this distance is small and the distribution of types is not highly concentrated in the (b^*, b') interval, then the chosen allocation performs better than the random allocation (and vice versa).

While the distribution of types may be unknown to the policy maker, there are a couple of sufficient conditions under which the chosen allocation is assured to perform better than the random allocation. These alternative conditions are:

Condition 1. The Constant scheme performs at least as good as the Streak incentive scheme in the *random allocation*, i.e. $\int_{b_{min}}^{b_{max}} \mathbb{E}[F_i^C]g(b_i)db_i \geq \int_{b_{min}}^{b_{max}} \mathbb{E}[F_i^S]g(b_i)db_i$.

Condition 2. The share p in the *random allocation* is at least as high as the share endogenously arising in the *chosen allocation*, i.e. $p \geq \int_{b_{min}}^{b'} g(b_i)db_i$.

The following proposition proves this claim.

Proposition 5 (Frequency) *If Condition 1 or Condition 2 are satisfied, then letting agents choose their incentive scheme yields a higher average expected meditation frequency than exogenously assigning agents to incentive schemes.*

The above proposition implies an asymmetry between using the Constant and Streak as default scheme. While it is never optimal to offer agents only the Constant scheme,

offering only the Streak might perform better than letting agents choose between the two schemes if Streak performs better than Constant on average.

2.2.5 From theory to experiments

The theoretical results provide us with predictions that we can test in the experiment. Our main hypotheses are that i) both the Constant and Streak incentive schemes increase average meditation frequency compared to no monetary incentives (Proposition 1), ii) subjects sort according to their expected meditation benefits (Proposition 3) and iii), given that our experimental design can ensure Condition 2, letting people choose their incentive scheme increases average meditation frequency compared to the random allocation (Proposition 5).

3 Experimental Design

The experiment was pre-registered (AEARCTR-0004881). We conducted the experiment at the University of Amsterdam in two waves – in fall 2019 and winter 2020.¹⁸ The study was advertised as a well-being program. Participants were recruited on campus, via the mailing list of the CREED laboratory, and via social media. To be eligible, participants were required to be students and fluent in Dutch. In total, 511 participants participated in the study. We excluded 12 participants because we could not verify their student status, leading to a final sample of 499 participants. Out of these, 154 were male and 345 were female. Participants were predominantly Bachelor students and on average about 21 years old. At baseline, they meditated on average 0.43 days per week, and reported a meditation frequency goal of 3.25 days per week.

Table 1 presents the timeline of the experiment. Students who completed the consent form were invited to complete the baseline survey. The survey was incentivized with €10, received conditional upon completion of baseline and endline survey. The baseline survey consisted of two parts. In the first part, participants answered questions related to their mental health, meditation motivation and behavior, economic preferences and demographics, in that order. As part of mental health, we measured participants' mindfulness level, perceived stress, academic self-concept and self-esteem using questions of validated

¹⁸Subjects in both waves are overall very similar and only notably differ in gender and time preferences (cf. Table F1).

Table 1: Timeline of Experiment

Event	1st wave	2nd wave
Baseline survey	Oct 28, 2019 – Nov 1, 2019	Feb 3, 2020 – Feb 7, 2020
First meditation day	Nov 04, 2019	Feb 10, 2020
1st feedback email	Nov 13, 2019	Feb 19, 2020
2nd feedback email	Nov 20, 2019	Feb 28, 2020
3rd feedback email	Dec 01, 2019	Mar 08, 2020
Final feedback email	Dec 10, 2019	Mar 17, 2020
Endline survey	Dec 10, 2019 – Dec 14, 2019	Mar 17, 2020 – Mar 21, 2020
Meditation platform	Dec 10, 2019 – Dec 31, 2020	Mar 17, 2020 – Dec 31, 2020
Follow-up survey	Mar 19, 2020 – Mar 25, 2020	Jun 25, 2020 – Jul 1, 2020

psychological scales.¹⁹ We then measured participants’ motivation to meditate, asked them about their past meditation frequency and desired number of weekly meditation sessions for the near future. We also elicited participants’ risk preferences, desirability of control, age, gender and study program.²⁰ Summary statistics are shown in Table 2.

In the second part of the baseline survey, participants were first randomized into one of three treatments: *Control*, *Random* and *Choice*. All participants were then introduced to the 36-day online-based meditation program. They received explanations on the procedures of the meditation program and were shown a sample meditation session. Participants in *Control* received access to the meditation audio files and did not receive any monetary incentives for the completion of meditation sessions. Participants in *Random* were randomly allocated to either the Constant or Streak scheme. Participants in *Choice* could choose between the two schemes.²¹ To increase power, we calibrated the scheme shares in *Random* to equal the expected shares in *Choice* based on pilot data. Under the Constant scheme, participants were paid €2 for each day that they completed the ‘meditation of the day’ session. Under the Streak reward, participants received €8

¹⁹Specifically, we used the Mindfulness Attention Awareness scale (Brown and Ryan, 2003), the Perceived Stress Scale (Cohen et al., 1983), and six questions each from the Academic Self-Concept Scale (Reynolds, 1988) and the Self-Esteem Scale (Rosenberg, 2015).

²⁰We extracted six questions from the Intrinsic Motivation Inventory Scale (Ryan, 1982) to measure motivation to meditate. We used the investment method by Gneezy and Potters (1997) to measure risk preferences and extracted six questions from the Desirability of Control Scale (Burger and Cooper, 1979).

²¹We chose this design as it allows us to cleanly identify both the effect of incentives and the effect of choice on meditation frequency in a way that closely resembles real-world applications. An alternative design in which all incentivized subjects have to choose and their choices are implemented only with a certain likelihood would convolute results by a possible disappointment effect of being asked to choose and then not listened to.

Table 2: Summary Statistics

	(1) <i>Control</i>	(2) <i>Random</i>	(3) <i>Choice</i>	(4) <i>p</i> -value (1) <i>vs.</i> (2&3)	(5) <i>p</i> -value (2) <i>vs.</i> (3)
<i>Demographics</i>					
Age	21.12	20.99	21.37	.83	.29
Female (0/1)	.66	.72	.69	.30	.50
Bachelor student (0/1)	.82	.80	.81	.79	.83
<i>Mental Health</i>					
Mindfulness (1-6)	3.29	3.23	3.27	.54	.55
Perceived stress (0-40)	20.81	20.36	19.60	.15	.25
Academic self-concept (1-7)	4.44	4.39	4.50	.89	.30
Self-esteem (10-40)	27.77	27.71	28.42	.54	.20
<i>Economic Preferences</i>					
Investment in risky asset (0-40)	22.59	22.31	22.82	.99	.67
Short-run discount factor β	.97	.97	.97	.53	.72
Long-run discount factor δ	.95	.96	.96	.56	1.00
Desirability of Control (1-7)	4.52	4.50	4.67	.37	.04
<i>Meditation Behavior</i>					
Intrinsic motivation to meditate (1-7)	4.58	4.61	4.80	.27	.16
Current meditation frequency (days/wk)	.54	.42	.33	.12	.37
Meditation frequency goal (days/wk)	3.19	3.17	3.40	.69	.38
Observations	165	163	171		

Note: Column 1 depicts means of *Control*, columns 2 and 3 are the means of *Random* and *Choice*. Columns 4 (resp. 5) show the *p*-values from *t*-tests or tests of proportions with respect to the differences between *Control* and the two incentive treatments (resp. between *Random* and *Choice*). Numbers for the short-run discount factors only include 430 observations as 59 subjects did not complete the endline survey and we excluded 10 subjects that had multiple switching points in one of the two multiple price lists.

upon completion of a 3-day meditation streak. To complete a 3-day streak, participants had to complete meditation sessions on three consecutive days. Once a participant has completed a 3-day streak, the count is set back to zero. Subsequently, we elicited participants' beliefs about their expected number of completed meditation sessions during the intervention period.²²

The 36-day meditation program lasted from November 1, 2019 until December 9, 2019 (1st wave) and from February 10, 2020 until March 16, 2020 (2nd wave). On each day of

²²Subjects received €1 if they were exactly correct in their prediction.

the meditation program, subjects received an email with a link to the ‘meditation of the day’. Meditations were provided by the lifestyle app of a large Dutch health insurance company. All meditation sessions were guided and took between 5 and 15 minutes. We included a timer on the meditation page. Sessions for incentivized participants were only counted as completed if the participant answered the test question correctly and spent a sufficient amount of time (at least equal to the length of the meditation audio file minus 40 seconds) on the meditation page.²³ To account for the fact that participants in the control group had no incentive to answer the test question (correctly), we acted conservatively, counting as completed every started session of a non-incentivized participant, unless the timer proved that the participant had not spent a sufficient amount of time on the meditation page.²⁴ This implies that our estimates for the effect of incentives are, if anything, a lower bound for the true effect. Every ten days, participants received a feedback email that listed the number of completed meditations up to that day. Participants in *Random* and *Choice* additionally received information about their accumulated earnings.

We sent out the endline survey one day after the last meditation day. It included the same questions about mental health and motivation to meditate as in the baseline survey. Additionally, we elicited participants’ time preferences via multiple price lists. In the second wave, we also included additional questions, e.g. about the perceived experimenter’s goal of the intervention, that aimed to help analyze potential explanations for the surprising treatment effect of *Choice* compared to *Random*. Finally, all participants gave feedback on their experiences during the study. On the same day, participants received access to all meditation audio files of the study and were informed about their total earnings. A couple of days later, participants were paid out. Precisely one hundred days after the endline survey, participants received a short follow-up survey that asked them about their current number of meditation days per week.

²³As an example of a test question, one day’s question was: *What did you practice with this meditation?* – a) *Setting intentions*, b) *Breathing*, c) *Gratitude*.

²⁴We believe this measure has enough accuracy since control group participants did not have incentives to pretend the start of a meditation they did not intend to complete, as they obtained no monetary benefits from doing so.

4 Experimental Results

We hereby present the results of the experiment. In section 4.1, we present the results about the effect of incentives on meditation frequency. In section 4.2, we explore selection into incentive schemes, and in section 4.3, we analyze the effect of letting participants choose their incentive scheme on meditation frequency.

4.1 The Effect of Monetary Incentives

Confirming our prediction based on Proposition 1, monetary incentives increase meditation frequency during the intervention period both on the intensive and extensive margin. During the intervention period, subjects who are randomly assigned to the Constant resp. Streak incentive scheme complete on average 22.70 resp. 22.74 meditation sessions, while subjects in the control group complete on average 11.50 sessions (see panel *a* in Figure 2). The differences are statistically significant (both $p = 0.000$ in the two-sided t -test). On the extensive margin, 97% of subjects who are assigned to Constant and Streak complete at least one meditation session compared to 85% of non-incentivized subjects (panel *b*). The differences are again statistically significant ($p = 0.007$ resp. $p = 0.003$ in the two-sided test of proportions).²⁵

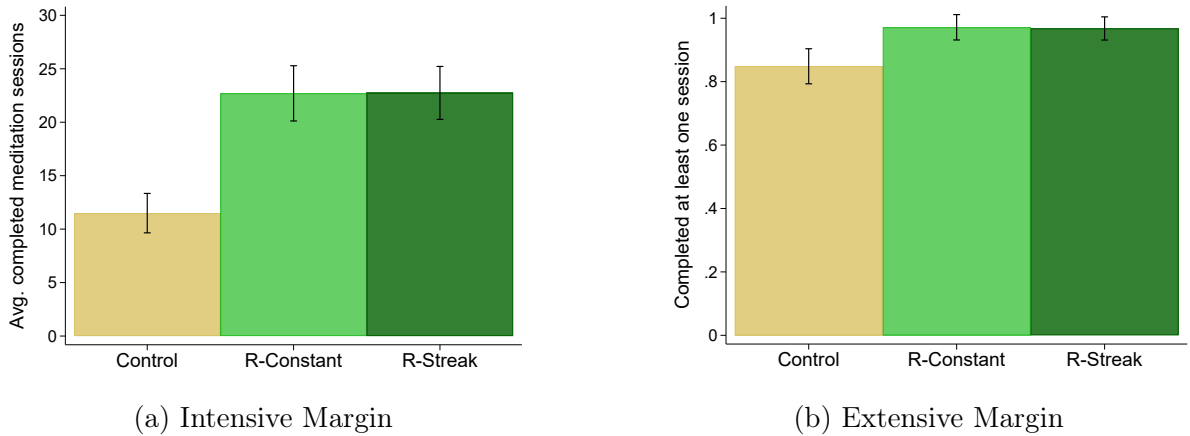
While the two incentive schemes increase meditation frequencies to almost the same extent on average, they differ in whose frequencies are most affected. In line with the single-crossing property (Proposition 2), subjects with high benefits of meditation meditate more when randomly assigned to the Streak and subjects with low benefits meditate more when randomly assigned to the Constant incentive scheme (see Figure F3).²⁶ Regressing completed meditation sessions on Streak (vs. Constant) assignment and meditation benefits as well as their interaction term shows that the net effect of Streak is increasing significantly in benefits ($p = 0.043$ of the interaction term).

All in all, we find that monetary incentives increase meditation frequency on the

²⁵Even though the intervention period of the second wave fell into the beginning of the Covid-19 pandemic, the treatment effects of the first and second wave are very similar (cf. Table F2).

²⁶As we cannot directly observe the benefits of meditation, we make use of a proxy measure. Our proxy *benefits* is the principal component of a subject's weekly meditation goal and her intrinsic motivation as measured by averaging responses over 6 questions extracted from the well-established Intrinsic Motivation Inventory Scale (Ryan, 1982). Both measures are taken prior to the introduction of the incentive schemes so that *benefits* is thus unaffected by the choice or allocation of the schemes. *benefits* is a viable proxy for actual benefits as Spearman's rho of completed meditation sessions and *benefits* in *Control* equals $\rho = 0.215$ ($p = 0.006$).

Figure 2: Effect of Incentives



Note: The left panel shows average meditation frequencies during the intervention period for non-incentivized subjects (sand), and subjects that are randomly assigned to the Constant (light green) and Streak (dark green) incentive schemes. The right panel shows the share of subjects that completed at least one meditation session during the intervention period. The black bars indicate 95% confidence intervals.

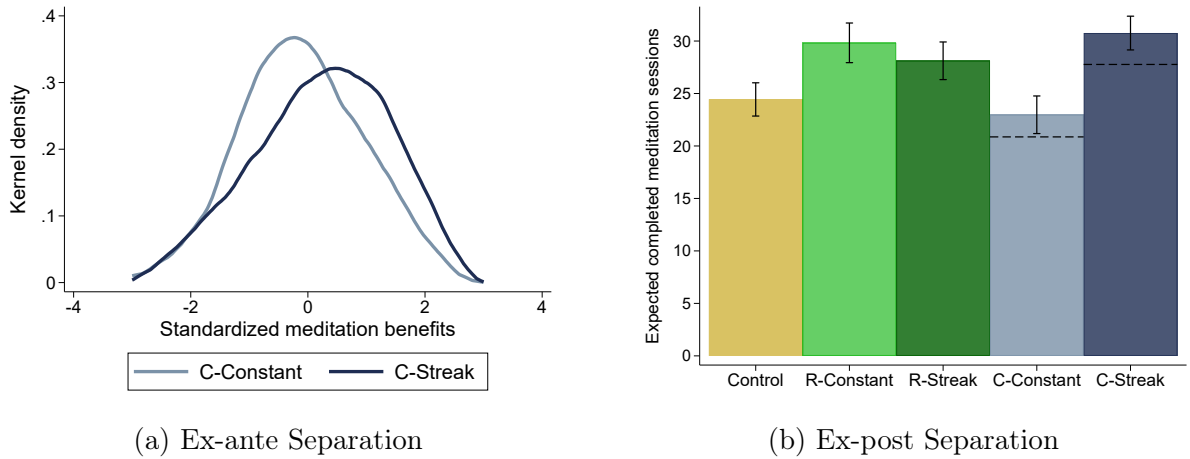
intensive and extensive margin during the intervention period. We also find evidence that subjects in *Random* react with different intensities to the two incentive schemes in the predicted direction depending on their meditation benefits. Put together, our experimental results suggest that monetary incentives are a viable tool to make people meditate more.

4.2 Separation

According to our model, the channel through which *Choice* should lead to a higher meditation frequency than *Random* is through the sorting of subjects in the two schemes according to their benefits from meditation. Subjects with high benefits should self-select into the Streak scheme, which allows them to reap larger rewards given their high expected completion rates. For subjects with low benefits who have a low chance to complete a 3-day streak, it is more profitable to choose the safer albeit lower rewards brought about by the Constant scheme. According to theory (Proposition 3), self-selection in *Choice* should lead to *full separation*, i.e. the allocation by which subjects with net benefits below a certain threshold adopt the Constant scheme, and all others adopt Streak.

Out of the 171 subjects assigned to *Choice*, 96 (56.14%) chose Streak and 75 (43.86%) chose Constant. Do subjects choose in line with the separation hypothesis? Consistent

Figure 3: Separation



Note: The left panel depicts the kernel density distributions of standardized meditation benefits (with Epanechnikov kernel function and a half-width of 0.5), split by chosen incentive scheme. The right panel depicts average beliefs about completed meditation sessions during the intervention period, split by treatment and incentive scheme. The black bars indicate 95% confidence intervals. The dashed lines indicate average beliefs about completed meditation sessions under the counterfactual assumption that a participant had chosen the resp. other scheme.

with our theoretical prediction, subjects who choose Streak have significantly higher, by about one third of a standard deviation, standardized average meditation benefits than subjects who choose Constant (0.25 vs. -0.10, $p = 0.028$ in the two-sided t -test). The density distribution of subjects who chose Streak is of similar shape as the distribution of subjects who chose Constant but is shifted to the right as depicted in panel *a* of Figure 3. The two distributions are significantly different ($p = 0.024$ in the Kolmogorov-Smirnov test). Contrary to theory, however, the density distributions show a substantial degree of overlapping. The lack of full separation may indicate that some subjects do not fully understand the relationship between their choice of incentive scheme, meditation benefits and expected meditation rates.²⁷ In addition, it could be driven by unmodeled properties of the preferences such as risk and time preferences.²⁸

We also find evidence for there being a fraction of subjects that fall in the (b^*, b') interval, i.e. subjects that choose the Constant scheme but would have achieved a higher meditation frequency with the Streak scheme. Our data show that the fraction of subjects

²⁷Note, however, that there was a comprehension check in the baseline survey to ensure that all subjects understand the rules of the incentive schemes.

²⁸In Figure F2 we show that the Streak scheme leads to larger volatility in payoffs. However, risk preferences do not seem to be linked to the choice of the scheme (Spearman's rho of risk aversion and choosing Streak equals $\rho = 0.035$, $p = 0.647$). Similarly, choosing Streak is not linked to time discounting (in money) (Spearman's rho of short-run discount factor and choosing Streak equals $\rho = 0.040$, $p = 0.630$).

who chooses Constant is larger than the fraction of subjects who meditates more under the Constant scheme. Figure F1 depicts that the Streak scheme achieves higher meditation frequencies than the Constant scheme for subjects above the 35th percentile. However, 44% of subjects select the Constant scheme when given the choice.

4.2.1 Ex-post Separation

A second form of separation occurs after the allocation of incentive schemes (either by choice or randomly). The Streak incentive scheme gives comparatively larger returns to high completion rates leading to a compound effect of selection and scheme-specific incentives. Accordingly, the theory predicts that there is a larger difference between the average expected meditation rates of *Choice-Streak* and *Choice-Constant*, than there is between *Random-Streak* and *Random-Constant* (Proposition 4).²⁹

Right after the allocation of incentive schemes, we elicit participants' (incentivized) beliefs about how many sessions they expect to successfully complete during the 36-day intervention period. Our findings confirm the theoretical prediction as shown in panel *b* of Figure 3. While average beliefs do not significantly differ between schemes in *Random* ($p = 0.199$ in the two-sided *t*-test, and $p = 0.504$ in the Kolmogorov-Smirnov test), subjects who choose Streak expect to complete significantly more meditation sessions than subjects who choose Constant (30.76 vs. 22.97; the difference is significant with $p = 0.000$ in both the two-sided *t*-test and the Kolmogorov-Smirnov test).

To sum up, the theoretical predictions are confirmed in the data. There is partial separation into incentive schemes based on meditation benefits and an even more pronounced ex-post separation based on expected meditation frequencies.

4.3 The Effect of *Choice*

We now turn to the question of whether *Choice* leads to higher average meditation frequency than *Random*. The two individually sufficient conditions for expecting a positive effect of *Choice* according to Proposition 5 are both satisfied in our experimental data. Condition 1 is satisfied as the Constant and Streak incentive scheme in *Random* yield almost the same average meditation frequency (22.70 vs. 22.74). Condition 2 is satisfied

²⁹Note that beliefs should coincide with actual meditation frequencies under the assumption of rational expectations.

because the quota of subjects in each incentive scheme is almost identical across the two incentivized treatments: 57.06% (resp. 56.14%) of subjects are paid the Streak incentive in *Random* (resp. *Choice*).³⁰ In the alternative model with time-inconsistent agents (Appendix C), a positive effect of *Choice* requires an additional condition, namely that individuals’ meditation benefits and present-bias parameters are independently distributed. Our data suggest that this is indeed the case in our experiment (Spearman’s rho between our proxies for meditation benefits and short-run discount factor equals $\rho = 0.018$, $p = 0.714$). While our data provide evidence in favor of only *partial separation* rather than *full separation*, Proposition A1 shows that under quota-preserving allocations, as is the case in the experiment, *Choice* is still expected to perform better than *Random*, irrespective of the degree of *partial separation*. The theory thus predicts an unambiguous superiority of *Choice* in boosting meditation frequencies.

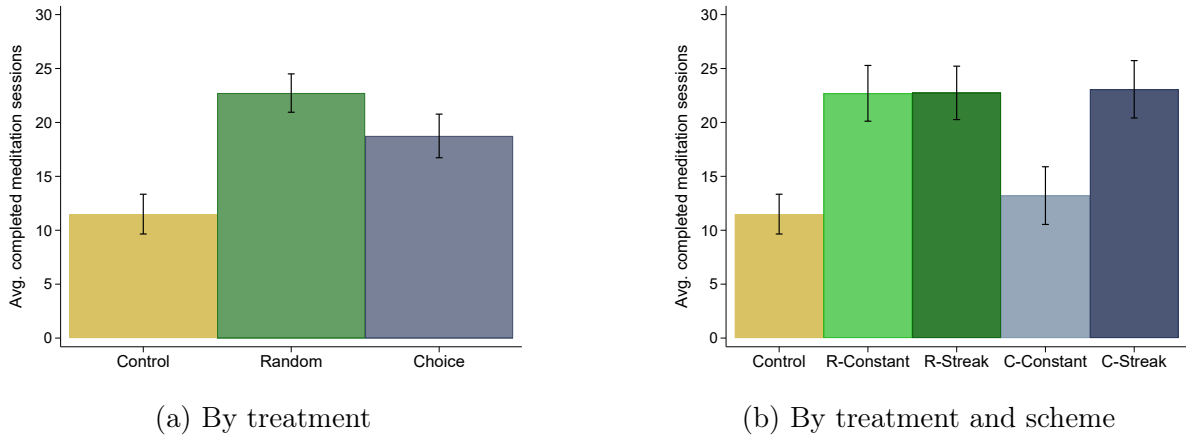
Experimental results are presented in panel *a* of Figure 4. Contrary to our predictions, letting subjects choose their incentive scheme leads to a lower (rather than a higher) average meditation frequency (18.75 for *Choice* vs. 22.72 for *Random*). The difference between the two incentivized treatments is statistically significant ($p = 0.004$ in the two-sided *t*-test).³¹ Splitting the incentivized treatments by incentive scheme, panel *b* of Figure 4 shows that the difference between *Random* and *Choice* is entirely driven by the differential performance of subjects in the Constant incentive scheme. Subjects who chose the Constant incentive scheme completed 13.13 sessions, a number statistically non-different from the completion rate in *Control* ($p = 0.301$ in the two-sided *t*-test). On the other hand, subjects who chose or were assigned to the Streak incentive scheme, as well as subjects randomly assigned to the Constant incentive scheme meditated an approximately equal and not statistically distinguishable number of sessions (22.85 on average across the three groups).

Interestingly, the treatment effect crucially hinges on subject’s meditation frequency prior to the study. We only find a negative effect of *Choice* compared to *Random* for subjects who did not meditate at baseline ($p = 0.000$ in the two-sided *t*-test); there is no effect for the about 20% of subjects who meditated at baseline at least once a week ($p = 0.344$

³⁰None of the results changes if we re-weight observations in *Random* to control for the slightly different shares of subjects across the two treatments.

³¹The treatment effect is not modulated by how much subjects desire to maintain a sense of control, according to the desirability of control index as shown in Table F3. We also do not find different effects of *Choice* by gender ($p = 0.925$).

Figure 4: Meditation Frequencies



Note: The figure depicts average number of completed meditation sessions during the intervention period split by treatment (left panel) and treatment and incentive scheme (right panel). The black bars denote 95% confidence intervals.

in the two-sided t -test). Indeed, a regression of completed meditation sessions on dummy variables identifying *Choice* and a strictly positive meditation frequency at baseline as well as their interaction term shows that letting people choose works significantly better for subjects who meditate at baseline ($p = 0.012$ of the interaction term) as depicted in Table F3.

5 Understanding the Negative Effect of *Choice*

The comparatively poor performance of *Choice* runs contrary to our theoretical predictions. In this section, we dive into possible explanations for this unexpected finding. We start by ruling out the hypothesis of bad selection (i.e., subjects sorting incorrectly into schemes), leveraging a set of results that coherently point in this direction. Having ruled out selection effects, we conclude that the negative effect of *Choice* is *psychological* (presumably activated by the act of choosing), and propose a suggestive list of channels through which such effect can operate.

5.1 Ruling out Selection Effects

Based on three pieces of evidence, a convincing case can be made that the poor performance of *Choice* is not due to bad selection. First, as extensively discussed in section 4.2, subjects who choose Streak have on average higher meditation benefits than subjects who

choose Constant. The sorting according to meditation benefits is not only theoretically predicted to increase the performance of *Choice*; it is also empirically validated by data from the *Random* treatment where we see that participants with high (resp. low) meditation benefits indeed meditate more under the Streak (resp. Constant) scheme (Figure F3). It is important to point out that the selection we observe is not full but only partial. However, while partial separation does weaken the expected positive treatment effect of *Choice*, it cannot explain why *Choice* performs significantly worse than *Random* (cf. Proposition A1).

Additional evidence in favor of favorable selection is that elicited beliefs about expected meditation frequencies are significantly higher than counterfactual beliefs, i.e. beliefs regarding the meditation frequency that would occur had the subject been assigned to the scheme that they did *not* choose.³² Counterfactual beliefs are estimated right after actual beliefs and could not be incentivized by construction. Taken at face value, they reveal that subjects believe that their chosen scheme enables them to meditate more often than their not-chosen scheme, in accordance with the separation hypothesis.

Lastly, the negative effect of *Choice* plotted against quantiles of meditation frequency is most pronounced for medium meditation frequencies (as shown in Figure F4). This is at odds with the hypothesis of anti-selection (i.e., sorting that runs opposite to theoretical predictions), as we would then observe a comparatively more negative effect of *Choice* at the extremes of the distribution, where the mismatch between incentive schemes and types is largest.

5.2 Psychological Effects

Having ruled out adversarial selection effects, we infer that the poor performance of *Choice* is due to psychological factors, presumably instilled by the act of choosing itself. In what follows we provide a list of suggestive explanations. The potential channels discussed in this section are not part of the pre-registered analysis, they should be seen as exploratory in nature and serving as a conceptual map for future research. Due to psychological richness of the setup, we also do not view this list as exhaustive.

One possible explanation is the potential demotivating effect associated with choosing

³²The average beliefs in *Choice* are 27.34 completed meditation sessions; while average counterfactual beliefs in *Choice* are 24.74 completed sessions ($p = 0.000$ in the two-sided t -test).

the *less challenging* Constant incentive scheme. Since the Constant scheme pays less than the Streak scheme for high meditation rates, a subject that chooses Constant may, by this very act, reveal to herself (and to the policy maker) that she is targeting a low completion rate. This (self-)signaling or expectation can in turn become self-fulfilling and lead to lower meditation frequency in *Choice* compared to *Random*.³³ Our data can be cautiously interpreted in favor of this hypothesis. The detrimental effect of self-signaling should be particularly pronounced for inexperienced subjects as they are the ones who have not yet formed a stable self-image about what type of meditator they are. This prediction is supported by the finding that the negative effect of choice is entirely driven by (inexperienced) subjects who did not meditate at baseline. Further, self-signaling is also predicted to decrease beliefs about meditation frequency of subjects who chose the Constant scheme. Indeed, there is a large gap between the beliefs of subjects choosing Constant and those randomly assigned to it (cf. panel *b* in Figure 3). Note, however, that subjects randomly assigned to and actively selecting into the Constant scheme are not directly comparable with each other due to selection. To control for selection, we therefore compare beliefs in *Random-Constant* with a combination of beliefs in *Choice*, namely *actual* beliefs of subjects who chose Constant and *counterfactual* beliefs of subjects who chose Streak.³⁴ We find that beliefs in *Random-Constant* are significantly higher than the combined beliefs in *Choice* (29.83 vs. 25.67; $p = 0.001$).

Another possible channel is regret aversion. Throughout the intervention, subjects in *Choice* may recall their counterfactual earnings, i.e. their payoffs had they chosen the other scheme. This in turn may make them reluctant to engage in a meditation pattern that would have earned them more money under the scheme they have not chosen. In particular, subjects in *Choice-Constant* may refrain from meditating three times in a row to avoid the regret of having lost the extra-payment of €2 that they would have earned under Streak. We explore this hypothesis by studying meditation patterns on days that would mark a complete streak, dubbed ‘Decisive Days’. Table F4 shows that, irrespective of the specification, subjects who chose the Constant incentive scheme are not less (or

³³From a conceptual viewpoint, a self-signaling channel could also be entertained for subjects selecting into the Streak scheme, who would derive a boost in motivation to meditate. Arguably, however, offering monetary incentives implicitly expects participants to meditate often. Because of this, the Streak might act as the default scheme, so that choosing Constant becomes a much stronger signal than choosing Streak.

³⁴We elicited non-incentivized counterfactual beliefs in *Choice* by asking about subjects’ expectation regarding how often they would have meditated with the incentive scheme that they had *not* chosen.

more) likely to meditate on a day that would complete a streak than subjects who were randomly assigned to Constant. In other words, we do not observe unusual low completion rates on the third day of a streak by subjects who have chosen the Constant scheme. We thus do not find evidence in favor of the regret aversion hypothesis.

A third potential explanation might be due to the differing presentation of incentive schemes in the baseline survey in *Random* and *Choice*. In *Random*, subjects only got to see the incentive scheme they were assigned to. In *Choice*, subjects got to see both schemes. This difference could cause subjects in *Random* and *Choice* to entertain different beliefs about the intervention along several dimensions, e.g. regarding the policy maker’s main intention with the intervention and her sophistication about the efficacy of incentives. Additionally, comparing incentive schemes could alter subjects’ perception about the size of the incentives compared to seeing only one incentive scheme. We explore these hypotheses with a non-incentivized questionnaire added to the end of the endline survey.³⁵ We find that none of the questions shows any notable difference between *Random* and *Choice* (see Table F5). These findings make it unlikely that the poor performance of *Choice* is driven by differences in the presentation of incentive schemes.

A fourth potential explanation for the poor performance of *Choice* is that subjects have a general dislike for making choices when it comes to selecting their incentive scheme. We do not find evidence for this explanation either. On the contrary, 86% of the subjects in *Choice* indicate in the endline survey that they would prefer to choose their incentive scheme again if possible in the future.

6 Conclusion

Monetarily incentivizing individuals to undertake behavioral change has proved an effective policy for improving physical health and well-being. Although early interventions have been traditionally based on a one-size-fit-all approach, recent logistical and technological advancements make it feasible for policy makers to customize incentive schemes to fit the specific needs and constraints of different individuals. In the presence of asymmetric information, when individuals have private knowledge about their preferences for undertaking a certain behavior, the policy maker may find it advantageous to leave the

³⁵This questionnaire was distributed only to subjects in the second wave.

choice of incentive schemes to the individuals themselves. In this paper, we theoretically analyze the opportunity of exogenously assigning one of two incentive schemes, vis-à-vis the alternative approach of letting participants select the incentive scheme for themselves. We further derive conditions under which letting participants choose is predicted to increase the overall adherence to the policy intervention.

We test these predictions in a field experiment designed to increase adherence to a daily mindfulness meditation program disseminated among the student population at the University of Amsterdam. The study compares the effect of a Constant incentive scheme that remunerates subjects for each completed meditation session to that of a Streak scheme that pays subjects a larger amount but only if they complete three sessions in a row. The study further compares the effect of letting subjects choose between the two schemes to a setting where the allocation is decided randomly. We find that the two incentive schemes perform equally well on average and significantly increase meditation frequency compared to the non-incentivized control group. We further find that letting subjects choose their incentives leads to self-selection into the two schemes in partial accordance with the theoretical prediction. However, in contrast to our predictions, letting subjects choose their incentives surprisingly leads to lower meditation frequency than distributing the incentives randomly. Interestingly, the negative effect of choice is entirely driven by subjects who did not meditate at baseline. Our data allows to rule out the poor self-selection into incentive schemes as the reason for the negative effect of *Choice*. We infer that the negative effect must be due to psychological factors, presumably associated with the act of choosing. We conclude by suggestively indicating several potential channels through which this can operate. While our data speculatively suggest a potential effect of negative self-signaling by subjects choosing the less challenging Constant scheme, we do not find support for alternative explanations such as regret aversion, differences in presentation and dislike of choice.

All in all, our paper thus shows that monetary incentives are a viable tool to change individual's behavior not only in the physical but also in the mental health domain. The innovative Streak scheme proves a good alternative to the more standard Constant scheme, however, it also does not outperform the latter on average. While our theoretical model shows that, under mild assumptions, choice should work better than a random allocation, our experimental results act as a cautionary tale against letting, in particular

inexperienced, individuals choose between incentive schemes. Policy makers may consider implementing a short try-out-period in which individuals are able to gain experience with the targeted activity before the actual choice is made, as successfully implemented with commitment contracts ([Royer et al., 2015](#); [Sadoff and Samek, 2019](#)). However, more research is needed on the general relationship between choosing incentives and prior experience with the targeted behavior.

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Online Appendix

A Proofs and Additional Theoretical Results

Proof of Proposition 1 (Incentive effect) \leftarrow Recall that $m_c > 0$, $m_s > 0$ by assumption. Note that $v_i^* = \sqrt{(1+b_i+m_s)^2 - 2m_s} - 1 - b_i = \sqrt{(1+b_i)^2 + 2b_i + m_s^2} - 1 - b_i > 0$. It follows that $q_i > 0$ and $1 - q_i > 0$. Then $\mathbb{E}[F_i^C] = b_i + m_c > b_i = \mathbb{E}[F_i^B]$ and $\mathbb{E}[F_i^S] = q_i(b_i + v_i^*) + (1 - q_i)(b_i + m_s) > b_i = \mathbb{E}[F_i^B]$. Similarly, $\mathbb{E}[E_i^C] = \frac{1}{2}(b_i + m_c)^2 > \frac{1}{2}b_i^2 = \mathbb{E}[E_i^B]$ and $\mathbb{E}[E_i^S] = \frac{1}{2}(b_i + v_i^*)^2 > \frac{1}{2}b_i^2 = \mathbb{E}[E_i^B]$. Therefore, both the Constant and Streak incentive scheme increase an agent's expected meditation frequency and expected utility. ■

Proof of Proposition 2 (Single crossing) \leftarrow Define $\mathbb{E}[D_i] = \mathbb{E}[F_i^S] - \mathbb{E}[F_i^C]$ as the difference between an agent's expected meditation frequency under a Streak and Constant incentive scheme. Taking the first derivative of $\mathbb{E}[D_i]$ w.r.t. b_i yields

$$\begin{aligned} \frac{\partial \mathbb{E}[D_i]}{\partial b_i} &= \frac{\partial \left(\frac{\sqrt{(1+b_i+m_s)^2 - 2m_s} - 1}{\sqrt{(1+b_i+m_s)^2 - 2m_s}} (1 + b_i + m_s) - (b_i + m_c) \right)}{\partial b_i} \\ &= \frac{2m_s}{((1 + b_i + m_s)^2 - 2m_s)^{\frac{3}{2}}} > 0. \end{aligned}$$

By definition, $\mathbb{E}[F_i^C(b^*)] = \mathbb{E}[F_i^S(b^*)]$. Therefore, it holds that $\forall i : b_i < b^* \Rightarrow \mathbb{E}[F_i^C] > \mathbb{E}[F_i^S]$ and $\forall i : b_i > b^* \Rightarrow \mathbb{E}[F_i^C] < \mathbb{E}[F_i^S]$. ■

Proof of Proposition 3 (Separation) \leftarrow Recall that $\mathbb{E}[U_i^C] = \frac{1}{2}(b_i + m_c)^2$ and $\mathbb{E}[U_i^S] = \frac{1}{2}(b_i + v_i^*)^2$. As type b' is defined as being indifferent between the Constant and Streak incentive scheme, it holds that $v_i^*(b') = \sqrt{(1+b'+m_s)^2 - 2m_s} - 1 - b' = m_c$. Rearranging yields $b' = \frac{m_c^2 + 2m_c - m_s^2}{2(m_s - m_c)}$. Further, note that all agents for whom $v_i^* < m_c$ choose the Constant incentive scheme and all agents for whom $v_i^* > m_c$ choose the Streak incentive scheme. Taking the derivative of v_i^* w.r.t. b_i gives $\frac{1+b_i+m_s}{\sqrt{(1+b_i+m_s)^2 - 2m_s}} - 1 > 0$. Therefore, it holds that $\forall i : b_i < b' \Rightarrow v_i^* < m_c$ and $\forall i : b_i > b' \Rightarrow v_i^* > m_c$. Thus, all agents with $b_i < b'$ choose the Constant and all agents with $b_i > b'$ choose the Streak incentive scheme. ■

Proof of Proposition 4 (Ex-post separation) \leftarrow Denote the average expected meditation frequency of agents that choose Constant resp. Streak by $\mathbb{E}[F^{Ch,C}]$ and $\mathbb{E}[F^{Ch,S}]$. Similarly, denote the average expected meditation frequency of agents

that are randomly assigned to Constant resp. Streak by $\mathbb{E}[F^C]$ and $\mathbb{E}[F^S]$. Clearly, $\mathbb{E}[F^C] = \int_{b_{\min}}^{b_{\max}} \mathbb{E}[F_i^C]g(b_i)db_i$ and $\mathbb{E}[F^S] = \int_{b_{\min}}^{b_{\max}} \mathbb{E}[F_i^S]g(b_i)db_i$. As all agents for which $b_i < b'$ choose Constant and all agents $b_i > b'$ choose Streak (Proposition 3), $\mathbb{E}[F^{Ch,C}] = \frac{\int_{b_{\min}}^{b'} \mathbb{E}[F_i^C]g(b_i)db_i}{G(b')}$ and $\mathbb{E}[F^{Ch,S}] = \frac{\int_{b'}^{b_{\max}} \mathbb{E}[F_i^S]g(b_i)db_i}{1-G(b')}$. As $\frac{\mathbb{E}[F_i^C]}{\partial b_i} = 1 > 0$ and $\frac{\partial \mathbb{E}[F_i^S]}{\partial b_i} = \frac{2m_s}{((1+b_i+m_s)^2-2m_s)^{\frac{3}{2}}} + 1 > 0$, $\mathbb{E}[F^{Ch,C}] < \mathbb{E}[F^C]$ and $\mathbb{E}[F^{Ch,S}] > \mathbb{E}[F^S]$. ■

Proof of Proposition 5 (Frequency) ← First, recall from (Proposition 3) that all agents with $b_i < b' = \frac{m_c^2+2m_c-m_s^2}{2(m_s-m_c)}$ choose the Constant incentive scheme and all agents with $b_i > b'$ choose the Streak incentive scheme. The difference between an agent's expected meditation frequency under a Streak and Constant incentive scheme is increasing in b_i , i.e. $\frac{\partial \mathbb{E}[D_i]}{\partial b_i} > 0 \forall i$ (cf. Proof of Proposition 2).

Condition 1: First, we reformulate $\mathbb{E}[F^{Ch}] = \int_{b_{\min}}^{b_{\max}} \mathbb{E}[F_i^C]g(b_i)db_i + \int_{b'}^{b_{\max}} \mathbb{E}[D_i]g(b_i)db_i$. As $\int_{b_{\min}}^{b_{\max}} \mathbb{E}[F_i^C]g(b_i)db_i \geq \int_{b_{\min}}^{b_{\max}} \mathbb{E}[F_i^S]g(b_i)db_i$, $\mathbb{E}[F^{Ra}] \leq \int_{b_{\min}}^{b_{\max}} \mathbb{E}[F_i^C]g(b_i)db_i$. As $\frac{\partial \mathbb{E}[D_i]}{\partial b_i} > 0 \forall i$, $b' > b^*$ and $\mathbb{E}[D_i(b^*)] = 0$, it follows that $\int_{b'}^{b_{\max}} \mathbb{E}[D_i]g(b_i)db_i > 0$ and thus $\mathbb{E}[F^{Ch}] > \mathbb{E}[F^{Ra}]$.

Condition 2: Reformulate $\mathbb{E}[F^{Ra}] = \int_{b_{\min}}^{b_{\max}} \mathbb{E}[F_i^C]g(b_i)db_i + (1-p) \int_{b_{\min}}^{b_{\max}} \mathbb{E}[D_i]g(b_i)db_i$. Thus, $\mathbb{E}[F^{Ch}] - \mathbb{E}[F^{Ra}] = \int_{b'}^{b_{\max}} \mathbb{E}[D_i]g(b_i)db_i - (1-p) \int_{b_{\min}}^{b_{\max}} \mathbb{E}[D_i]g(b_i)db_i$. Clearly, $\int_{b'}^{b_{\max}} \mathbb{E}[D_i]g(b_i)db_i = \int_{b'}^{b_{\max}} g(b_i)db_i \frac{\int_{b'}^{b_{\max}} \mathbb{E}[D_i]g(b_i)db_i}{\int_{b'}^{b_{\max}} g(b_i)db_i} \geq (1-p) \int_{b_{\min}}^{b_{\max}} \mathbb{E}[D_i]g(b_i)db_i$ as $\int_{b'}^{b_{\max}} g(b_i)db_i \geq 1-p$ and $\frac{\partial \mathbb{E}[D_i]}{\partial b_i} > 0 \forall i$. It follows that $\mathbb{E}[F^{Ch}] \geq \mathbb{E}[F^{Ra}]$.

Therefore, letting agents choose their incentive scheme yields a higher average expected meditation frequency than exogenously assigning agents to incentive schemes if Condition 1 or 2 are satisfied. ■

We now present an additional theoretical result. We show that letting agents choose their incentive scheme increases average expected meditation frequency compared to a quota-preserving random allocation also under imperfect separation.

Proposition A1 (Frequency with partial separation) *Denote an agent's probability to choose Constant by ρ_i . Define partial separation by $\rho_i \in (0, 1) \forall i$ and $\frac{\partial \rho_i}{\partial b_i} < 0$. If agents partially separate, then letting agents choose their incentive scheme yields a higher average expected meditation frequency than a quota-preserving random allocation.*

Proof of Proposition A1 (Frequency with partial separation) Take any arbitrary pair of agents j and k such that $b_j > b_k$ and exactly one of the two agents

has chosen the Constant incentive scheme while the other agent has chosen the Streak incentive scheme. The average expected meditation frequency of agents j and k under partial separation then equals $\mathbb{E}[F_{j,k}^{PS}] = \frac{\rho_j(1-\rho_k)}{\rho_j(1-\rho_k)+(1-\rho_j)\rho_k}(\mathbb{E}[F_j^C] + \mathbb{E}[F_k^C] + \mathbb{E}[D_k]) + \frac{(1-\rho_j)\rho_k}{\rho_j(1-\rho_k)+(1-\rho_j)\rho_k}(\mathbb{E}[F_j^C] + \mathbb{E}[D_j] + \mathbb{E}[F_k^C])$. Now, assume instead that agents j and k are randomly reassigned one each to the Constant and Streak incentive scheme to match the shares in the random allocation to the shares in the chosen allocation. The average meditation frequency of agents j and k then equals $\mathbb{E}[F_{j,k}^{Ra}] = \frac{1}{2}(\mathbb{E}[F_j^C] + \mathbb{E}[F_k^C] + \mathbb{E}[D_k]) + \frac{1}{2}(\mathbb{E}[F_j^C] + \mathbb{E}[D_j] + \mathbb{E}[F_k^C])$. Subtracting $\mathbb{E}[F_{j,k}^{Ra}]$ from $\mathbb{E}[F_{j,k}^{PS}]$ gives $\mathbb{E}[F_{j,k}^{PS}] - \mathbb{E}[F_{j,k}^{Ra}] = \frac{(\rho_k - \rho_j)(D_j - D_k)}{2(\rho_j(1-\rho_k) + (1-\rho_j)\rho_k)} > 0$ as $b_j > b_k$ and $\frac{\partial \rho_i}{\partial b_i} < 0$ implies that $D_j > D_k$ (cf. Proof of Proposition 2) and $\rho_k < \rho_j$. As random reassignment decreases the average expected meditation frequency of every reassigned pair, letting agents choose their incentive scheme under partial separation thus yields a higher average expected meditation frequency. ■

B Welfare

An agent's per-period welfare equals $W_{it} = b_i + e - c_{it}$ if she meditates and $W_{it} = 0$ if she does not meditate. Under the Constant incentive scheme, an agent's expected per-period welfare thus equals

$$\mathbb{E}[W_i^C] = \int_0^{b_i+m_c} (b_i + e - c_{it}) dc_{it} = \frac{1}{2}(b_i^2 - m_c^2) + e(b_i + m_c). \quad (4)$$

Similarly, the expected per-period welfare under the Streak incentive scheme equals

$$\begin{aligned} \mathbb{E}[W_i^S] &= q_i \int_0^{b_i+v_i^*} (b_i + e - c_{it}) dc_{it} + (1 - q_i) \int_0^{b_i+m_s} (b_i + e - c_{it}) dc_{it} \\ &= \frac{1}{1 + b_i + v_i^*} \left(\frac{1}{2}(b_i^2 - (v_i^*)^2) + e(b_i + v_i^*) \right) + \frac{b_i + v_i^*}{1 + b_i + v_i^*} \left(\frac{1}{2}(b_i^2 - m_s^2) + e(b_i + m_s) \right). \end{aligned} \quad (5)$$

Similar to frequency, in order to make the policy maker's decision between exogenous assignment and choice non-trivial, we assume that not for all types welfare is higher under Constant nor Streak. We now show that if the externality is sufficiently large, the single-crossing result in terms of meditation frequency (Proposition 2) carries over to welfare.

Proposition B1 (Single crossing – Welfare) *If $m_s < e + \frac{e}{2b_i+2e+1} \forall i$, there is a threshold type b^{**} such that for all $b_i > b^{**}$ (resp. $b_i < b^{**}$), welfare is higher (resp. lower) under the Streak than under the Constant incentive scheme.*

Proof of Proposition B1 (Single crossing – Welfare) We show that $\frac{\partial(\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])}{\partial b_i} > 0$ if $m_s \leq e + \frac{e}{2b_i+2e+1} \forall i$. $\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C] = \frac{1}{1+b_i+v_i^*}(ev_i^* - \frac{1}{2}(v_i^*)^2) + \frac{b_i+v_i^*}{1+b_i+v_i^*}(em_s - \frac{1}{2}m_s^2) - (em_c - \frac{1}{2}m_c^2)$. As $\frac{\partial v_i^*}{\partial b_i} > 0$ (see Proof of Proposition 3), $\frac{\partial(\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])}{\partial b_i} > 0$ if $em_s - \frac{1}{2}m_s^2 > ev_i^* - \frac{1}{2}(v_i^*)^2$. Substituting $v_i^* = \sqrt{(1 + b_i + m_s)^2 - 2m_s} - 1 - b_i$ and reformulating, the condition becomes $m_s < e + \frac{e}{2b_i+2e+1}$. By assumption, $\exists b^{**}$ s.t. $\mathbb{E}[W_i^S(b^{**})] = \mathbb{E}[W_i^C(b^{**})]$. Therefore, it holds that $\forall i : b_i < b^{**} \Rightarrow \mathbb{E}[W_i^C] > \mathbb{E}[W_i^S]$ and $\forall i : b_i > b^{**} \Rightarrow \mathbb{E}[W_i^C] > \mathbb{E}[W_i^S]$ if $m_s < e + \frac{e}{2b_i+2e+1} \forall i$. ■

The proposition implies that welfare is increased if agents with high meditation benefits are incentivized with the Streak and agents with low benefits with the Constant incentive scheme as long as the externality is sufficiently large compared to the Streak reward.

Arguably, the condition is not very restrictive. If the targeted behavior exerts only a small externality, then there is little reason for a policy maker to even intervene in the first place. If the externality is relatively too small, then welfare under a Streak incentive scheme no longer monotonously increases in meditation benefits as agents with high benefits meditate excessively in second streak-periods.

In order to derive results for the effect of choice on welfare, we also need to consider how agents choose their incentive schemes. As agents are selfish and thus only care about their own utility, they are ignorant towards whether the policy maker cares about meditation frequency or welfare, which implies that Proposition 3 still holds under a welfare objective. Similar to a frequency objective, there is also a wedge between the welfare-maximizing threshold b^{**} and the actual separating threshold b' . Recall that for the indifferent type b' it holds that $v_i^* = m_c$. Substituting $v_i^*(b')$ for m_c and b' for b_i into the difference of $\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C]$, we obtain $\mathbb{E}[W_i^S(b')] - \mathbb{E}[W_i^C(b')] = \frac{b'+v_i^*(b')}{1+b'+v_i^*(b')} (em_s - \frac{1}{2}m_s^2 - (ev_i^*(b') - \frac{1}{2}v_i^*(b')^2))$. This expression is positive if $em_s - \frac{1}{2}m_s^2 \geq ev_i^*(b') - \frac{1}{2}v_i^*(b')^2$ resp. $m_s \leq 2e - v_i^*(b')$, which is the case if $m_s \leq \frac{2e(b'+e+1)}{2b'+2e+1}$ as $v_i^*(b') = \sqrt{(1+b'+m_s)^2 - 2m_s} - 1 - b'$, coinciding with the second part of the condition stated in Proposition B1. Thus, whenever the single crossing property for welfare holds, $b^{**} < b'$. In this case, agents in the interval (b^{**}, b') choose Constant but ought to choose Streak from an overall welfare perspective.

Given these results, we can now derive the welfare consequences of offering agents a choice between the Constant and Streak incentive scheme. Similar to meditation frequency, there are two additional sufficient conditions under which the chosen allocation is assured to perform better than the random allocation:

Condition B1. The Constant scheme yields weakly higher average welfare than the Streak incentive scheme in the *random allocation*,

$$\text{i.e. } \int_{b_{min}}^{b_{max}} \mathbb{E}[W_i^C]g(b_i)db_i \geq \int_{b_{min}}^{b_{max}} \mathbb{E}[W_i^S]g(b_i)db_i.$$

Condition B2. The share p in the *random allocation* is at least as high as the share endogenously arising in the *chosen allocation*, i.e. $p \geq \int_{b_{min}}^{b'} g(b_i)db_i$.

Proposition B2 (Welfare) *If $m_s < e + \frac{e}{2b_i+2e+1} \forall i$ and Condition B1 or Condition B2 are satisfied, then letting agents choose their incentive scheme yields a higher welfare than exogenously assigning agents to incentive schemes.*

Proof of Proposition B2 (Welfare) The proof closely follows that of Proposition 5.

Condition 1: Reformulate $\mathbb{E}[W^{Ch}] = \int_{b_{min}}^{b_{max}} \mathbb{E}[W_i^C]g(b_i)db_i + \int_{b'}^{b_{max}} (\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])g(b_i)db_i$.

As $\int_{b_{min}}^{b_{max}} \mathbb{E}[W_i^C]g(b_i)db_i \geq \int_{b_{min}}^{b_{max}} \mathbb{E}[W_i^S]g(b_i)db_i$, $\mathbb{E}[W^{Ra}] \leq \int_{b_{min}}^{b_{max}} \mathbb{E}[W_i^C]g(b_i)db_i$. As $\frac{\partial(\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])}{\partial b_i} > 0 \forall i$ if $m_s < \frac{2e(b_i+e+1)}{2b_i+2e+1}$ (see Proof of Proposition B1), $b' > b^{**}$ and $\mathbb{E}[W_i^S(b^{**})] - \mathbb{E}[W_i^C(b^{**})] = 0$, it follows that $\int_{b'}^{b_{max}} (\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])g(b_i)db_i > 0$ and thus $\mathbb{E}[W^{Ch}] > \mathbb{E}[W^{Ra}]$ if $m_s < e + \frac{e}{2b_i+2e+1} \forall i$.

Condition 2: Reformulate

$\mathbb{E}[F^{Ra}] = \int_{b_{min}}^{b_{max}} \mathbb{E}[W_i^C]g(b_i)db_i + (1-p) \int_{b_{min}}^{b_{max}} (\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])g(b_i)db_i$. Thus, $\mathbb{E}[W^{Ch}] - \mathbb{E}[W^{Ra}] = \int_{b'}^{b_{max}} (\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])g(b_i)db_i - (1-p) \int_{b_{min}}^{b_{max}} (\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])g(b_i)db_i$.

Clearly, $\int_{b'}^{b_{max}} (\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])g(b_i)db_i = \int_{b'}^{b_{max}} g(b_i)db_i \frac{\int_{b'}^{b_{max}} (\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])g(b_i)db_i}{\int_{b'}^{b_{max}} g(b_i)db_i} \geq (1-p) \int_{b_{min}}^{b_{max}} (\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])g(b_i)db_i$ as $\int_{b'}^{b_{max}} g(b_i)db_i \geq 1-p$ and $\frac{\partial(\mathbb{E}[W_i^S] - \mathbb{E}[W_i^C])}{\partial b_i} > 0 \forall i$ if $m_s < \frac{2e(b_i+e+1)}{2b_i+2e+1}$. It follows that $\mathbb{E}[W^{Ch}] \geq \mathbb{E}[W^{Ra}]$ if $m_s < \frac{2e(b_i+e+1)}{2b_i+2e+1}$.

Therefore, letting agents choose their incentive scheme yields a higher average welfare than exogenously assigning agents to incentive schemes if $m_s < \frac{2e(b_i+e+1)}{2b_i+2e+1}$ and Condition B1 or B2 are satisfied. ■

The proposition implies that offering agents a choice between Constant and Streak not only increases meditation frequency but also welfare if certain very similar conditions are met. Their similarities justify using frequency as a more easily observed proxy for welfare.

C Time Inconsistency

The model in the main text specifies that agents meditate inefficiently at baseline because they do not take the positive externality on the policy maker into account. This section instead assumes that the inefficiency is caused by an internality, namely time-inconsistent behavior. To allow for time-inconsistent behavior, we need to change the model in that an agent who meditates in period t obtains benefits b_i and potential rewards m_c resp. m_s only delayed in period $t + 1$. As is standard in the literature on time inconsistency, we further assume that agents have quasi-hyperbolic preferences (Phelps and Pollak, 1968; Laibson, 1997; O'Donoghue and Rabin, 1999). The present value of discounted future utilities to agent i in period t is then given by

$$U_{it} = u_{it} + \beta_i \sum_{s=t+1}^{\infty} \delta_i^{s-t} u_{is}. \quad (6)$$

where β_i denotes an agent's short-run and δ_i the long-run discount factor. For ease of exposition, we assume that $\delta_i = 1$. For simplicity, we focus our analysis on naive agents. Such agents are present-biased, i.e. $0 < \beta_i < 1$, but wrongfully believe that they are time-consistent, as indicated by their perceived short-run discount factor $\hat{\beta}_i = 1$. At baseline, an agent meditates inefficiently whenever $b_i > c_{it} > \beta_i b_i$. Because of this, a policy maker can increase welfare by monetarily incentivizing agents to meditate more.

As agents are naive, they expect to behave as if they were rational agents. This implies that, ceteris paribus, naive agents choose the same incentive scheme as rational agents. This implies that the indifferent type is unaltered by introducing naive agents, thus $b'(\beta_i) = b'(1)$. Proposition 3 therefore carries over to a setting with naive agents. While naive agents choose the same incentive scheme as rational agents, their meditation behavior differs. With the constant incentive scheme, naive agent i meditates in period t if and only if $\beta_i(b_i + m_c) \geq c_{it}$. Her expected meditation frequency is thus $\mathbb{E}[F_i^C(\beta_i)] = \beta_i(b_i + m_c)$. Similarly, with the streak incentive scheme, naive agent i meditates in second streak-periods if and only if $\beta_i(b_i + m_s) \geq c_{it}$. This yields an expected meditation frequency in second streak-periods of $\mathbb{E}[F_i^{S2}(\beta_i)] = \beta_i(b_i + m_s)$. As a naive agent in a first streak-period believes to meditate in a second streak-period (and all subsequent periods) as if she was a rational agent, option value $v_i^* = \sqrt{(1 + b_i + m_s)^2 - 2m_s} - 1 - b_i$ is unaltered. However, as option value v_i^* quantifies a future payoff, it is also discounted by β_i . This implies that

naive agent i meditates in first streak-periods if and only if $\beta_i(b_i + v_i^*) \geq c_{it}$, so that her expected meditation frequency in first streak-periods equals $\mathbb{E}[F_i^{S1}(\beta_i)] = \beta_i(b_i + v_i^*)$. As the likelihood of meditating in a first streak-period is altered by time inconsistency, so is the likelihood of agent i being in a second streak-period. This likelihood is given by $(1 - q_i(\beta_i)) = q_i(\beta_i)\beta_i(b_i + v_i^*)$, so that $q_i(\beta_i) = \frac{1}{1 + \beta_i(b_i + v_i^*)}$. The resulting expected meditation frequency with a streak incentive scheme is therefore $\mathbb{E}[F_i^S(\beta_i)] = q_i(\beta_i)\beta_i(b_i + v_i^*) + (1 - q_i(\beta_i))\beta_i(b_i + m_s) = \frac{\beta_i\sqrt{(1+b_i+m_s)^2-2m_s-1}}{\beta_i\sqrt{(1+b_i+m_s)^2-2m_s+1-\beta_i}}(1 + \beta_i(b_i + m_s))$. As with rational agents, the single-crossing property also holds with naive agents.

Proposition C1 (Single crossing – Time Inconsistency) *There is a threshold type $b^*(\beta_i)$ such that for all $b_i > b^*(\beta_i)$ (resp. $b_i < b^*(\beta_i)$), the expected meditation frequency is larger (resp. lower) under the Streak than under the Constant incentive scheme.*

Proof of Proposition C1 (Single crossing – Time Inconsistency) ← Define $\mathbb{E}[D_i(\beta_i)] = \mathbb{E}[F_i^S(\beta_i)] - \mathbb{E}[F_i^C(\beta_i)]$ as the difference between an agent's expected meditation frequency under a Streak and Constant incentive scheme. Taking the first derivative of $\mathbb{E}[D_i(\beta_i)]$ w.r.t. b_i yields

$$\begin{aligned} \frac{\partial \mathbb{E}[D_i(\beta_i)]}{\partial b_i} &= \frac{\partial \left(\frac{\beta_i\sqrt{(1+b_i+m_s)^2-2m_s-1}}{\beta_i\sqrt{(1+b_i+m_s)^2-2m_s+1-\beta_i}}(1 + \beta_i(b_i + m_s)) - \beta_i(b_i + m_c) \right)}{\partial b_i} \\ &= \frac{\beta_i \left(1 + b_i + m_s - \sqrt{(1 + b_i + m_s)^2 - 2m_s} \right) \left(1 + \beta_i(b_i + m_s) + \beta_i\sqrt{(1 + b_i + m_s)^2 - 2m_s} \right)}{\sqrt{(1 + b_i + m_s)^2 - 2m_s} \left(\beta\sqrt{(1 + b_i + m_s)^2 - 2m_s} + 1 - \beta_i \right)^2} > 0. \end{aligned}$$

By definition, $\mathbb{E}[F_i^C(b^*(\beta_i))] = \mathbb{E}[F_i^S(b^*(\beta_i))]$. Therefore, it holds that $\forall i : b_i < b^*(\beta_i) \Rightarrow \mathbb{E}[F_i^C(\beta_i)] > \mathbb{E}[F_i^S(\beta_i)]$ and $\forall i : b_i > b^*(\beta_i) \Rightarrow \mathbb{E}[F_i^C(\beta_i)] < \mathbb{E}[F_i^S(\beta_i)]$. ■

While introducing naive agents does not affect the single crossing property, the threshold type changes. As $\mathbb{E}[F_i^C(\beta_i)] = \beta_i\mathbb{E}[F_i^C(1)]$ but $\mathbb{E}[F_i^S(\beta_i)] = q_i(\beta_i)\beta_i(b_i + v_i^*) + (1 - q_i(\beta_i))\beta_i(b_i + m_s) < q_i\beta_i(b_i + v_i^*) + (1 - q_i)\beta_i(b_i + m_s) = \beta_i\mathbb{E}[F_i^S(1)]$ if $\beta_i < 1$ as $q_i(\beta_i) > q_i(1)$ and $v_i^* < m_s$, it holds that $b^*(\beta_i) > b^*(1)$ if $\beta_i < 1$. As $b'(\beta_i) = b'(1)$, the wedge between the desired threshold optimally chosen by the policy maker and the actual separating threshold chosen by the agents is lower for naive than for rational agents. The comparative statics, however, stay unchanged as $b^*(\beta_i) < b'(\beta_i)$. To see why, we plug m_c into $\mathbb{E}[F_i^S(b'(\beta_i))]$. This yields $\mathbb{E}[F_i^S(b'(\beta_i))] = \frac{1 + \beta_i(b'(\beta_i) + m_s)}{1 + \beta_i(b'(\beta_i) + m_c)}\beta_i(b'(\beta_i) + m_c) > \beta_i(b'(\beta_i) + m_c) = \mathbb{E}[F_i^C(b'(\beta_i))]$. As $\frac{\partial[\mathbb{E}[F_i^S(\beta_i)] - \mathbb{E}[F_i^C(\beta_i)]]}{\partial b_i} > 0 \forall i$, it follows that $b^*(\beta_i) < b'(\beta_i)$.

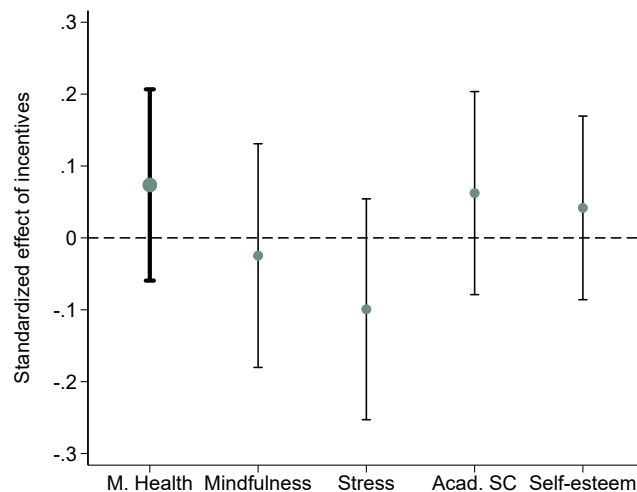
If agents' present bias is homogeneous or agents' benefits and present bias are independent, then all further results (see Propositions 4 and 5) from the main text carry over to the setting with (a subset of) naive agents. Interestingly, the relative (positive) effect of choice on average expected meditation frequency becomes larger with naive agents, as the wedge between $b^*(\beta_i)$ and $b'(\beta_i)$ narrows in agents' present bias. In contrast, if agents' benefits and present bias are not independent of each other, then it could be that choice yields lower frequency even when Conditions 1 or 2 are met. To illustrate, assume that there are only two agents i and j for whom $b_i > b_j$ and $\beta_i < \beta_j = 1$. If $b_i > b'(\beta_i) = b'(1) > b_j$, $b_i < b^*(\beta_i)$ and $b_j > b^*(1)$, then the chosen allocation yields lower expected meditation frequency than the random allocation that allocates one agent to each scheme; agent i (j) chooses the streak (constant) scheme but meditates more under the constant (streak) scheme.

D Mental Health Outcomes

This section discusses the effects of monetarily incentivizing subjects to meditate on several mental health outcomes. We elicited these outcomes in the baseline and endline surveys.

Figure D1 depicts the standardized effects of incentives along several mental-health-related dimensions. The figure shows that monetary incentives led to an increase of 0.07 standard deviations in our combined measure of mental health, which is, however, not significant ($p = 0.277$). Splitting up the combined measure into mindfulness level, perceived stress, academic self-concept and self-esteem, we observe that the incentives did not lead to a significant change in any of these measures.

Figure D1: Effect of Incentives on Mental Health Outcomes



Note: The figure depicts the standardized net effects of incentives on self-reported mental health, mindfulness, perceived stress, academic self-concept and self-esteem, controlling for baseline levels. Mental health is a combined measure of the other four outcome variables and is computed via a factor analysis. The black bars indicate 95% confidence intervals.

E Long-term Effects on Meditation Frequency

While our experiment was not designed to measure long-term effects of monetary incentives on meditation behavior, data from our 100-day follow-up survey allows us to estimate post-intervention effects. This analysis is complicated by uneven attrition in the control group and incentivized treatments.³⁶ However, if we assume that every subject who did not report their meditation frequency does not meditate in a typical week,³⁷ we find that there is no significant effect of monetary incentives on weekly meditation frequency 100 days after the end of the intervention (0.69 vs. 0.56, $p = 0.342$ in a two-sided t -test). The lack of long-term effects is in line with the great majority of papers in the literature (e.g. [Acland and Levy, 2015](#) & [März, 2019](#); [Carrera et al., 2018](#); [Woerner, 2021](#)).

³⁶Only 61% of subjects in the control group reported their weekly meditation frequency in a typical week, while 77% did so in the incentivized treatments.

³⁷This assumption is conservative, yet somewhat reasonable given that already 61% of subjects who completed the follow-up survey reported a meditation frequency of zero, and subjects who did not complete the follow-up survey had a significantly lower intrinsic motivation to meditate at baseline ($p = 0.018$) and completed much fewer meditation sessions during the intervention period (7.53 vs. 21.63, $p = 0.000$) than subjects who did report their weekly meditation frequency at follow-up.

F Additional Tables and Figures

Table F1: Summary Statistics By Wave

	(1) First Wave	(2) Second Wave	(3) <i>p</i> -value (1) vs. (2)
<i>Demographics</i>			
Age	21.05	21.33	.31
Female (0/1)	.73	.64	.02
Bachelor student (0/1)	.82	.80	.45
<i>Mental Health</i>			
Mindfulness	3.23	3.30	.24
Perceived stress	20.42	20.02	.48
Academic self-concept	4.49	4.38	.25
Self-esteem	28.10	27.80	.52
Desirability of Control	4.57	4.56	.84
<i>Economic Preferences</i>			
Risk preferences	22.56	22.61	.96
Time preferences	36.57	37.52	.01
<i>Meditation Behavior</i>			
Intrinsic motivation to meditate	4.67	4.64	.79
Current weekly meditation frequency	0.39	0.48	.39
Meditation frequency goal	3.26	3.25	.98
Observations	288	211	

Note: Columns 1 and 2 depict means of first-wave resp. second-wave subjects. Column 3 shows the *p*-values from *t*-tests or tests of proportions with respect to the differences in means.

Table F2: Effect of Incentives and Choice by Wave

Margin	Effect of Incentives		Effect of Choice	
	Intensive	Extensive	Intensive	Extensive
Mean of reference group	11.032	.849	22.796	.968
Constant	12.675*** (2.071)	.936** (.450)		
Streak	11.045*** (2.107)	.735** (.357)		
Choice			-4.551** (1.809)	-.611** (.303)
Wave	1.065 (1.888)	-.010 (.240)	-.167 (1.828)	.054 (.397)
Constant * Wave	-3.496 (3.251)	-.142 (.658)		
Streak * Wave	.443 (3.140)	.211 (.581)		
Choice * Wave			1.415 (2.758)	.166 (.486)
Observations	328	328	334	334
(Pseudo-) R^2	0.190	0.079	0.026	0.042

Note: The table shows OLS estimates in the first two columns and probit estimates in the last two columns. The dependent variable in the first and third column is the number of completed meditation sessions during the 36-day intervention period. The dependent variable in the second and fourth column indicates whether a subject completed at least one meditation session during the intervention period. The reference group in the first two columns is first-wave subjects in *Control*, the reference group in the last two columns is first-wave subjects in *Random*. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table F3: Heterogeneous Effects of *Choice*

	(1)	(2)	(3)
Standardized Desirability of Control	-.023 (.880)		
Female		6.556*** (2.034)	
Meditate at baseline			-2.894 (2.229)
<i>Choice</i>	-3.707*** (1.365)	-3.563 (2.496)	-5.578*** (1.513)
Standardized Desirability of Control * <i>Choice</i>	-1.119 (1.275)		
Female * <i>Choice</i>		-.276 (2.952)	
Meditate at baseline * <i>Choice</i>			8.471** (3.364)
Constant	22.724*** (.903)	17.978*** (1.772)	23.381*** (1.004)
Observations	334	334	334
R^2	0.030	0.078	0.043

Note: The table shows OLS estimates for the effect of *Choice* interacted with the standardized desirability of control measure (1), gender (2) and a non-zero meditation frequency at baseline (3). The reference group is subjects in *Random*. Robust standard errors clustered on the individual level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table F4: Meditation Frequency on ‘Decisive Days’

	(1)	(2)	(3)
Mean of reference group	.631	.619	.611
‘Decisive Day’	1.187*** (.195)	-.073 (.172)	-.253 (.189)
<i>Choice</i>	-1.066*** (.223)	-.504*** (.116)	-.362 (.098)
‘Decisive Day’ * <i>Choice</i>	.451 (.284)	.022 (.265)	.064 (.274)
Lagged days	0	3	7
Observations	5220	4785	4205
(Pseudo-) R^2	0.190	0.079	0.026

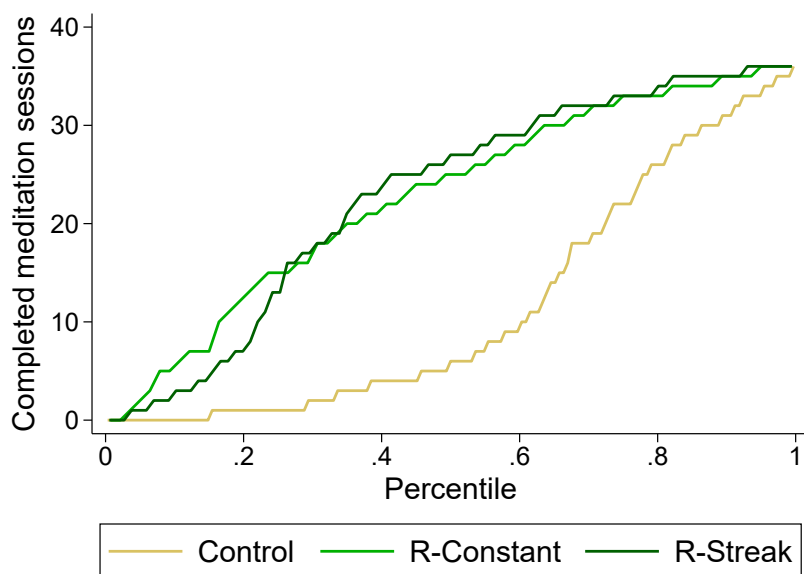
Note: The table shows logit estimates for the effect of ‘decisive days’ and *Choice* as well as their interaction term for subjects who have chosen the Constant incentive scheme. The reference group is subjects in *Random-Constant*. ‘Decisive days’ indicate days on which subjects could complete a 3-day streak. Robust standard errors clustered on the individual level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table F5: Conveyed Information

	(1) <i>Random</i>	(2) <i>Choice</i>	(3) p -value (1) vs. (2)
1. How much do you think that the experimenters are interested in helping you meditate as often as possible?	4.400	4.609	.48
2. How much do you think the experimenters are interested in helping you find the meditation frequency that is best for you?	4.385	4.547	.62
3. How knowledgeable do you think the experimenters are in giving you rewards for completing the sessions?	5.508	5.297	.37
4. What do you think about the size of the rewards for the meditation sessions?	4.846	4.625	.31
Observations	65	64	

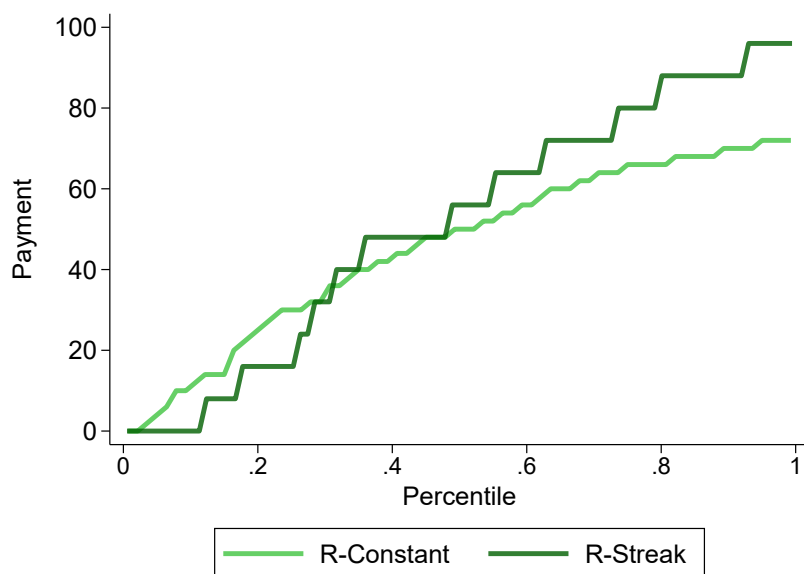
Note: Columns 1 and 2 depict means subjects in *Random* resp. *Choice*. Column 3 shows the p -values from t -tests with respect to the differences in means. Answers were reported on a 7-point Likert scale in the follow-up survey by second-wave subjects only. In questions 1-3 the scale goes from 1 (absolutely not) to 7 (absolutely/very much so). In question 4 the scale goes from 1 (very low) to 7 (very high). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure F1: Meditation Frequency over Percentiles



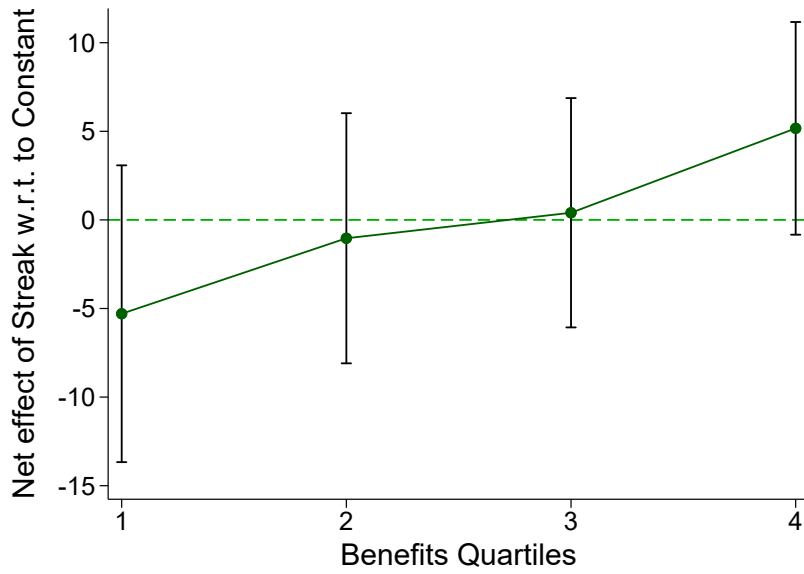
Note: The figure shows the meditation frequencies over percentiles for subjects in *Control* and *Random*, split by incentive scheme.

Figure F2: Distribution of Payments in *Random*



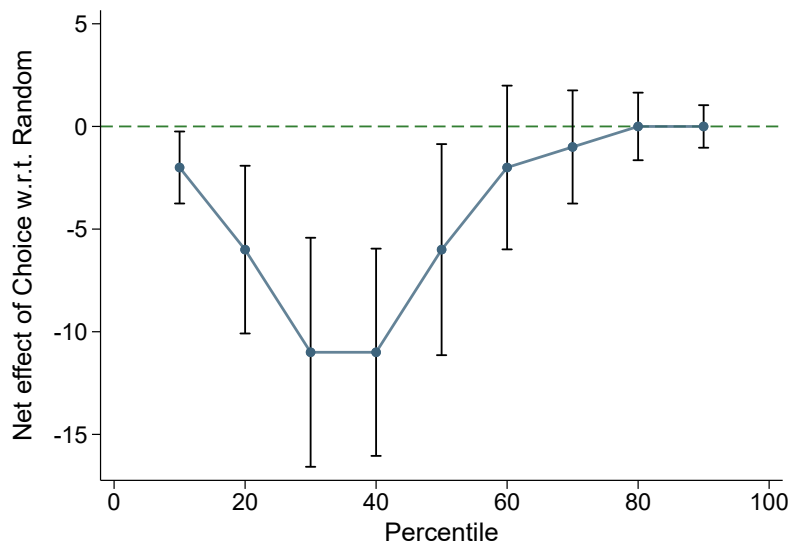
Note: The figure depicts the payment distributions across subjects randomly assigned to Constant and Streak.

Figure F3: Net Effect of Streak by Meditation Benefits



Note: The figure shows the net effect of Streak compared to Constant by *Benefits* quartile for subjects in *Random*. The black bars indicate 95% confidence intervals.

Figure F4: Net Effect of Choice by Percentile



Note: The figure shows the net effect of Choice compared to *Random* by percentile of completed meditation sessions. The black bars indicate 95% confidence intervals.