

## Digital Addiction<sup>†</sup>

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*Many have argued that digital technologies such as smartphones and social media are addictive. We develop an economic model of digital addiction and estimate it using a randomized experiment. Temporary incentives to reduce social media use have persistent effects, suggesting social media are habit forming. Allowing people to set limits on their future screen time substantially reduces use, suggesting self-control problems. Additional evidence suggests people are inattentive to habit formation and partially unaware of self-control problems. Looking at these facts through the lens of our model suggests that self-control problems cause 31 percent of social media use. (JEL D12, D61, D90, D91, I31, L86, O33)*

Digital technologies occupy a large and growing share of leisure time for people around the world. By some estimates, the average person with internet access spends more than two hours each day on social media, and there are now 3.8 billion social media users (Kemp 2020). In a 57-country survey, people now say they spend more time consuming online media than they do watching television (Zenith 2019). Americans check their smartphones 50 to 80 times each day (Deloitte 2018; Molla 2020; New York Post 2017).

A natural interpretation of these facts is that digital technologies provide tremendous consumer surplus. However, an increasingly popular alternative view is that

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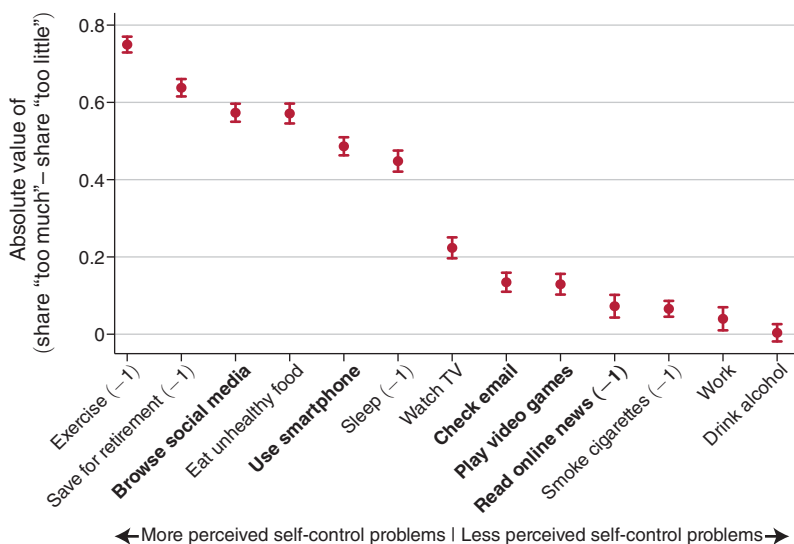


FIGURE 1. ONLINE AND OFFLINE TEMPTATION

*Notes:* This figure presents responses to the following question, which we asked participants in our experiment during the baseline survey, “For each of the activities below, please tell us whether you think you do it too little, too much, or the right amount.” The bars are ordered from left to right in order of largest to smallest absolute value of (share “too little” to share “too much”).

habit formation and self-control problems—what we call “digital addiction”—play a substantial role. Many argue that smartphones, video games, and social media apps may be harmful and addictive in the same ways as cigarettes, drugs, or gambling (Alter 2018; Newport 2019; Eyal 2020). The World Health Organization (2018) has listed digital gaming disorder as an official medical condition. Recent experimental studies find that social media use can decrease subjective well-being (SWB) (e.g., Mosquera et al. 2019; Allcott et al. 2020). Figure 1 shows that social media and smartphone use are two of the top five activities that a sample of Americans think they do “too little” or “too much.” Compared to the other three top activities ordered at left (exercise, retirement savings, and healthy eating), digital self-control problems have received much less attention from economists.<sup>1</sup>

The nature and magnitude of digital addiction matter for a number of important questions. Should people take steps to limit the amount of time they and their children spend on their smartphones and social media? What is the best way to design digital self-control tools? How can companies that make video games, social media, and smartphones best align their products with consumer welfare? Are proposed regulations such as the Social Media Addiction Reduction Technology (SMART) Act a good idea?<sup>2</sup>

<sup>1</sup> Among many important examples, see Charness and Gneezy (2009) and Carrera et al. (2021) on exercise, Madrian and Shea (2001) and Carroll et al. (2009) on retirement savings, and Sadoff, Samek, and Sprenger (2020) on healthy eating.

<sup>2</sup> This bill, introduced in 2019 by Republican Senator Josh Hawley, proposed to prohibit the use of design features such as infinite scroll and autoplay believed to make social media more addictive, and to require companies to default users into a limit of 30 minutes per day of social media use. See US Congress (2019).

In this paper, we formalize an economic model of digital addiction, use a randomized experiment to provide model-free evidence and estimate model parameters, and use the model to simulate the effects of habit formation and self-control problems on smartphone use. We focus on six apps that account for much of smartphone screen time and that participants report to be especially tempting: Facebook, Instagram, Twitter, Snapchat, web browsers, and YouTube. We refer to these apps as “FITSBY.”

Our model follows Gruber and Köszegi (2001); Gul and Pesendorfer (2007); Bernheim and Rangel (2004); and others in defining addiction as the combination of two key forces: habit formation and self-control problems. As in Becker and Murphy (1988), habit formation means that today’s consumption increases tomorrow’s demand. As in Laibson (1997) and others, self-control problems mean that people consume more today than they would have chosen for themselves in advance. These two forces are central to classic addictive goods such as cigarettes, drugs, and alcohol.

Our model allows for projection bias (Loewenstein, O’Donoghue, and Rabin 2003), where people choose as if they are inattentive to habit formation, as well as naïveté about self-control problems. As in Becker and Murphy (1988), people who perceive at least some habit formation would reduce consumption if they know the price will increase in the future, while projection bias would dampen that effect. As in many other models (see Ericson and Laibson 2019), people who are at least partially aware of self-control problems might want commitment devices to restrict future consumption, and people who are at least partially unaware will underestimate future consumption.

For our experiment, we used Facebook and Instagram ads to recruit about 2,000 American adults with Android smartphones and asked them to install Phone Dashboard, an app designed for our experiment that records smartphone screen time and allows participants to set screen time limits. Participants completed four surveys at three-week intervals—a baseline (survey 1) and three follow-ups (surveys 2, 3, and 4)—that included survey measures of smartphone addiction and SWB as well as predictions of future FITSBY use. Participants answered three text message survey questions per week and kept Phone Dashboard installed for six weeks after survey 4.

We independently randomized two treatments. The *bonus treatment* was a temporary subsidy of \$2.50 per hour for reducing FITSBY use during the three weeks between surveys 3 and 4. We informed people whether or not they were assigned to the bonus treatment in advance, on survey 2. The *limit treatment* made available screen time limit functionality in Phone Dashboard. Participants in this group could set personalized daily time limits for each app on their phone, with changes effective the next day. These limits forced participants to stop using the relevant app and in most cases could not be immediately overridden, unlike the flexible limits in existing tools such as Android’s Digital Wellbeing and iOS’s Screen Time. The surveys encouraged participants to set limits in line with their self-reported ideal screen time, but doing so was entirely optional. We used multiple price lists (MPLs) to elicit participants’ valuations of the bonus treatment and the limit functionality.

The bonus treatment had persistent effects that are consistent with habit formation. The bonus reduced FITSBY use by 56 minutes per day during the three weeks when the incentives were in effect, a 39 percent reduction from the control group

average. In the three weeks after the incentive had ended, the bonus treatment group still used 19 minutes less per day. In the three weeks after that, they used 12 minutes less per day.

Participants correctly predict habit formation: the effects of the bonus on predicted postincentive FITSBY use line up closely with the effects on actual use. However, in the three weeks between when the bonus was announced and when it took effect, there was only a modest (and possibly zero) anticipatory response, which is only 12 percent of what our model would predict for forward-looking habit formation without projection bias. These results are consistent with a form of projection bias in which consumers are aware of habit formation while consuming as if they are inattentive to it.<sup>3</sup>

We also find clear evidence that people have self-control problems and are at least partly aware of them. The limit treatment reduced FITSBY screen time by 22 minutes per day (16 percent) over 12 weeks. The effects decline slightly over the course of the experiment; this decline is consistent with some loss of motivation, but the fact that the decline is slight means that the effects are unlikely to be driven by confusion or temporary novelty. Although the experiment offered no incentive to set limits, 78 percent of participants set binding limits and continued using them through the final weeks of the experiment. This far exceeds take-up of almost all commitment devices studied in the literature reviewed by Schilbach (2019, Table 1). On average, participants were willing to give up \$4.20 for three weeks of access to the limit functionality, and when trading off the bonus versus a fixed payment, 24 percent said they valued the bonus more highly because they wanted to give themselves an incentive to reduce consumption. These distinct measures of commitment demand are correlated with each other and with survey measures of addiction and desire to reduce screen time.

Notwithstanding their demand for commitment, participants seem to slightly underestimate their self-control problems. The control group modestly but repeatedly underestimated their future FITSBY use in all of our surveys, even though use is fairly steady over time and we reminded them of recent past use before asking them to predict. On average, the control group underestimated next-period FITSBY use by 6.1 minutes per day, or about 4 percent.

To further evaluate whether our interventions reduced addiction in a way that participants perceive to be beneficial, we examine effects on a variety of survey outcomes. On both the main surveys and text messages, the bonus and limit treatments significantly reduced an index of smartphone addiction adapted from the psychology literature. For example, both treatment groups reported being less likely to use their phone longer than intended, use their phone to distract from anxiety or fall asleep, have difficulty putting down their phone, lose sleep from phone use, procrastinate by using their phone, and use their phone mindlessly. Both treatment groups reported improved alignment between ideal and actual screen time. The bonus treatment group also scored higher on an index of SWB, with statistically significant increases in components related to concentration and avoiding distraction

<sup>3</sup>This distinction between awareness and attention raises interesting questions about other evidence of projection bias. For example, Busse et al. (2015) find that people are more likely to buy a convertible on sunny days. On sunny days, do people have different beliefs about future weather or how much they would drive a convertible?

and statistically insignificant changes in measures of happiness, life satisfaction, anxiety, and depression. Finally, both treatments are well targeted in the sense that effects were more positive for people who report more interest in reducing their use and who score higher on our addiction measures at baseline.

In the final section of the paper, we look at these results through the lens of our structural model. The model allows us to translate our short-run experimental estimates into effects on long-run steady state behavior, to quantify the magnitude of the effects we observe in terms of economically meaningful parameters, and to decompose the role of different behavioral forces through counterfactuals. We first estimate the model parameters by matching key moments from the experiment. We model the limit treatment as eliminating share  $\omega$  of self-control problems, and for our primary estimates we conservatively assume  $\omega = 1$ . The estimates reflect our experimental results: substantial habit formation and self-control problems, substantial projection bias, and slight naïveté about self-control problems. We then evaluate how steady-state consumption would change in counterfactuals where we eliminate self-control problems. Without habit formation, a conservative estimate of the effect of self-control problems is the effect of giving people screen time limit functionality: 22 minutes per day. But habit formation amplifies the effect of self-control problems, as the increase in current consumption also increases future marginal utility. In the presence of habit formation, our primary model prediction is that eliminating self-control problems would reduce FITSBY use by 48 minutes per day, or 31 percent of baseline use. Alternative assumptions mostly imply more self-control problems, more attention to habit formation, and larger effects on use.

Our results should be interpreted with caution for several reasons. First, our experiment took place during the beginning of the COVID-19 pandemic. Our survey evidence suggests that this increased screen time but did not have clear effects on the magnitude of self-control problems. Furthermore, even as the pandemic evolved over the three-month experiment, average screen time and the treatment effects of the limit were fairly stable. Second, our estimates apply to the 2,000 people who selected into our experiment, and these people are not representative of US adults. When we reweight our estimates to more closely approximate national average demographic characteristics, the modeled effect of self-control problems increases. Third, our model's predictions of FITSBY use without self-control problems depend on assumptions such as linear demand and geometric decay of habit stock. Fourth, our analysis is partial equilibrium in the sense that we do not model network effects and other externalities across users. If one person's social media use increases others' use, such positive network externalities would magnify the effects of self-control problems on population-wide social media use. Finally, our surveys walked participants through a process of setting optional screen time limits that implemented their self-reported ideal screen time, and we hypothesize that simply offering time limit functionality without walking through that process would have had smaller effects.<sup>4</sup>

<sup>4</sup>While Carrera et al. (2021) show that take-up of commitment devices can be driven by experimenter demand effects or decision-making noise instead of perceived self-control problems, there are three reasons why their concerns are less likely to apply to our experiment. First, while Carrera et al. (2021) studied one-time take-up of an unfamiliar commitment contract, our participants repeatedly set and continually kept screen time limits over a 12-week period. Second, we estimate even larger perceived self-control problems using participants' valuations of

Our work builds on several existing literatures. We extend a distinguished literature documenting present focus in diverse settings including exercise, healthy eating, consumption-savings decisions, and laboratory tasks (Ericson and Laibson 2019).<sup>5</sup> Ours is one of a small handful of papers that estimate the parameters of a present focus model with partial naïveté using field (instead of laboratory) behavior.<sup>6</sup> The digital self-control problems we study are particularly interesting because this is one of the few domains where market forces have created commitment devices, such as blockers for smartphone apps, email, and Websites (Laibson 2018). Our results suggest additional unmet demand for these commitment devices.

We also extend a distinguished literature on habit formation. One set of papers documents persistent impacts of temporary interventions in settings such as academic performance, energy use, exercise, hand washing, political protest, smoking, recycling, voting, water use, and weight loss.<sup>7</sup> We provide evidence in an important new domain. A second set of papers test for forward-looking habit formation using belief elicitation or advance responses to future price changes, sometimes interpreting such forward-looking behavior as support for “rational” models of addiction.<sup>8</sup> We estimate anticipatory responses using an experimental approach that, like the one in Hussam et al. (2019), addresses many confounds that arise in observational data (Chaloupka and Warner 1999; Gruber and Köszegi 2001; Auld and Grootendorst 2004; Rees-Jones and Rozema 2020). Furthermore, we use our model to actually estimate the magnitude of projection bias, which is important because earlier studies that reject a null hypothesis of fully myopic habit formation could still be consistent with substantial projection bias.

Finally, we extend three literatures that speak directly to digital addiction. The first literature includes theoretical papers modeling temptation in digital networks (Makarov 2011; Liu, Sockin, and Xiong 2020). The second includes experimental papers studying the effects of social media use on outcomes such as SWB and academic performance.<sup>9</sup> The third studies the effects of digital self-control tools.<sup>10</sup> Hoong (2021) is particularly related, and is an important antecedent to our study.

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the bonus treatment, which leverages an alternative methodology favored by Carrera et al. (2021) as well as Acland and Levy (2012); Augenblick and Rabin (2019); Chaloupka, Levy and White (2019); Allcott et al. (2022); and Strack and Taubinsky (2021). Third, unlike Carrera et al. (2021), we find strong correlations between use of screen time limits and other measures of perceived self-control problems.

<sup>5</sup>This includes Read and Van Leeuwen (1998); Fang and Silverman (2004); Shapiro (2005); Shui and Ausubel (2005); Ashraf, Karlan, and Yin (2006); DellaVigna and Malmendier (2006); Paserman (2008); Gine, Karlan, and Zinman (2010); Duflo, Kremer, and Robinson (2011); Acland and Levy (2012); Andreoni and Sprenger (2012a,b); Augenblick, Niederle, and Sprenger (2015); Beshears et al. (2015); Goda et al. (2015); Kaur, Kremer, and Mullainathan (2015); Laibson et al. (2015); Royer, Stehr, and Sydnor (2015); Exley and Naecker (2017); Augenblick (2018); Kuchler and Pagel (2018); Toussaert (2018); Augenblick and Rabin (2019); Casaburi and Macchiavello (2019); Schilbach (2019); John (2019); and Sadoff, Savikhin Samek, and Sprenger (2020).

<sup>6</sup>To our knowledge, these are Allcott et al. (2022); Bai et al. (2018); Carrera et al. (2021); Chaloupka, Levy, and White (2019); and Skiba and Tobacman (2018).

<sup>7</sup>This includes Gerber, Green, and Shachar (2003); Charness and Gneezy (2009); Gine, Karlan, and Zinman (2010); Ferraro, Jose Miranda, and Price (2011); John et al. (2011); Allcott and Rogers (2014); Bernedo, Ferraro, and Price (2014); Acland and Levy (2015); Royer, Stehr, and Sydnor (2015); Fujiwara, Meng, and Vogl (2016); Levitt, List, and Sadoff (2016); Beshears and Milkman (2017); Brandon et al. (2017); Carrera et al. (2018); Allcott et al. (2020); Bursztyjn et al. (2019); Gosnell, List, and Metcalfe (2020); and Van Soest and Vollaard (2019).

<sup>8</sup>This includes Chaloupka (1991); Becker, Grossman and Murphy (1994); Gruber and Köszegi (2001); Acland and Levy (2015); Hussam et al. (2019); and Do and Jacoby (2020).

<sup>9</sup>This includes Sagioglu and Greitemeyer (2014); Tromholt (2016); Hunt et al. (2018); Vanman, Baker, and Tobin (2018); Mosquera et al. (2019); Allcott et al. (2020); and Collis and Eggers (2019).

<sup>10</sup>This includes Marotta and Acquisti (2017) and Acland and Chow (2018).



In a smaller-scale experiment, she pioneers the use of encouragement to adopt self-control tools, compares predicted and ideal use to actual use, and shows results consistent with significant self-control problems. Our paper helps to unify the previous empirical literature with a formal model of digital addiction, relatively large sample, multiple treatment arms that convincingly identify habit formation and self-control problems using several different strategies, and robust measurement of screen time and survey outcomes.

Section I sets up the model. Sections II–IV detail the experimental design, data, and model-free results. Section V presents the model estimation strategy and parameter estimates, and Section VI presents the modeled effects of temptation on time use.

## I. Model

The goal of the model is to formalize the meaning of “digital addiction” and foreshadow how we identify the model parameters using our experiment.

In each period  $t \leq T$ , consumers choose consumption of a good  $x_t$  sold at price  $p_t$  that delivers flow utility  $u_t(x_t; s_t, p_t)$ . To model habit formation, utility depends on a stock  $s_t$  of past consumption that evolves according to

$$(1) \quad s_{t+1} = \rho(s_t + x_t),$$

where  $\rho \in [0, 1)$  captures the strength of habit formation. Habit formation captures why temporary price changes generate persistent effects in our experiment.

To model self-control problems, we follow Banerjee and Mullainathan (2010) in modeling  $x$  as a temptation good. Before period  $t$ , consumers consider period  $t$  flow utility to be  $u_t(x_t; s_t, p_t)$ . In period  $t$ , however, consumers choose as if period  $t$  flow utility is  $u_t(x_t; s_t, p_t) + \gamma x_t$ , where  $\gamma \geq 0$  reflects the amount of temptation. If  $\gamma > 0$ , consumers choose more  $x_t$  in period  $t$  than they would choose in advance. This temptation good framework generates similar predictions to the quasi-hyperbolic model from Laibson (1997) and Gruber and Köszegi (2001), but it naturally matches our application to a single addictive good and yields simpler estimating equations where temptation is additively separable.

Consumers may misperceive temptation: before period  $t$ , consumers predict that in period  $t$ , they will consider flow utility to be  $u_t(x_t; s_t, p_t) + \tilde{\gamma} x_t$ . We say that consumers are fully naïve if  $\tilde{\gamma} = 0$ , and fully sophisticated if  $\tilde{\gamma} = \gamma$ . Partial naïveté captures why our experiment participants underestimate  $x_t$  when asked to predict in advance. Partial sophistication captures why our participants want commitment devices to change their future behavior.

Following Loewenstein, O'Donoghue, and Rabin (2003), we allow the possibility of projection bias, in which consumers choose as if to maximize a weighted average of utility given the current habit stock  $s_t$  and utility given the predicted habit stock  $\tilde{s}_r$  in future period  $r > t$ . We let  $\alpha$  denote the weight on the current habit stock, and thus the magnitude of projection bias. Projection bias captures why consumers in our experiment might not reduce consumption in anticipation of a known future price change. We assume that consumers are fully naïve about projection

bias; sophistication would introduce strategic incentives to adjust current consumption to offset future bias.<sup>11</sup>

Following O'Donoghue and Rabin (1999) and others, we solve for perception-perfect equilibrium strategies, where consumers maximize current utility given predictions of future behavior. Let  $x_t(s_t, \gamma, \mathbf{p}_t)$  denote a strategy of the period- $t$  self, which depends on habit stock, temptation, and the vector of future prices  $\mathbf{p}_t = \{p_t, p_{t+1}, \dots, p_T\}$ . Let  $\tilde{x}_r(s_r, \tilde{\gamma}, \mathbf{p}_r)$  be a consumer's *prediction*, as of period  $t < r$ , of her period- $r$  strategy. A strategy profile  $(x_0^*, \dots, x_T^*)$  is perception perfect if in each period  $t$

$$(2) \quad x_t^*(s_t, \gamma, \mathbf{p}_t) = \arg \max_{x_t} u_t(x_t; s_t, p_t) + \gamma x_t + \left[ \alpha \sum_{r=t+1}^T \delta^{r-t} u_r(\tilde{x}_r^*(s_t, \tilde{\gamma}, \mathbf{p}_r); s_t, p_r) + (1 - \alpha) \sum_{r=t+1}^T \delta^{r-t} u_r(\tilde{x}_r^*(\tilde{s}_r, \tilde{\gamma}, \mathbf{p}_r); \tilde{s}_r, p_r) \right],$$

where  $\delta \leq 1$  is the discount factor.

Predicted and actual consumption differ due to naïveté about temptation and projection bias and the resulting misprediction of habit stock. We assume that the equilibrium prediction  $\tilde{x}_r^*(s_r, \tilde{\gamma}, \mathbf{p}_r)$  is the solution to equation (2) with  $\alpha = 0$  and  $\gamma = \tilde{\gamma}$ . Predicted habit stock  $\tilde{s}_r$  evolves according to  $\tilde{s}_{r+1} = \rho(\tilde{s}_r + \tilde{x}_r^*(\tilde{s}_r, \tilde{\gamma}, \mathbf{p}_r))$ .<sup>12</sup> The “rational” habit formation model of Becker and Murphy (1988) is the special case with  $\alpha = 0$  and  $\tilde{\gamma} = \gamma = 0$ .

To estimate the model, we follow Becker and Murphy (1988) and Gruber and Köszegi (2001) in specializing to the case of quadratic flow utility:

$$(3) \quad u_t(x_t; s_t, p_t) = \frac{\eta}{2} x_t^2 + \zeta x_t s_t + \phi s_t + (\xi_t - p_t) x_t,$$

where  $\eta < 0$  measures the demand slope,  $\zeta$  regulates the extent of habit formation,  $\phi$  is the direct effect of habit stock on utility (which could be positive or negative), and  $\xi_t$  is a deterministic period-specific demand shifter. This can be microfounded by assuming that consumers have income  $w$  that they must spend in each period, and income not spent on  $x_t$  is spent on a numeraire  $c_t = w - p_t x_t$  that is additively separable in  $u_t$ . In this specification,  $u_t$  is in units of dollars per period.

<sup>11</sup>Loewenstein, O'Donoghue, and Rabin (2003, p. 1219) also assume naïveté about projection bias, writing that “because this time inconsistency derives solely from misprediction of future utilities, it would make little sense to assume that the person is fully aware of it.” We note that our formulation of projection bias is slightly different than in Loewenstein, O'Donoghue, and Rabin (2003): while their consumers' predictions of future consumption are biased due to projection bias, our consumers predict consumption accounting for habit formation, but choose as if they are inattentive to it. This matches our empirical results.

<sup>12</sup>Since the predicted equilibrium strategy  $\tilde{x}_r^*(s_r, \tilde{\gamma}, \mathbf{p}_r)$  conditions on the state  $s_r$  inherited at time  $r$ , it will be the same when evaluated in all periods  $t < r$ . However, the predicted *action* in period  $r$  is not generally the same when evaluated in all periods  $t < r$ , as the predicted  $\tilde{s}_r$  will differ by  $t$ .



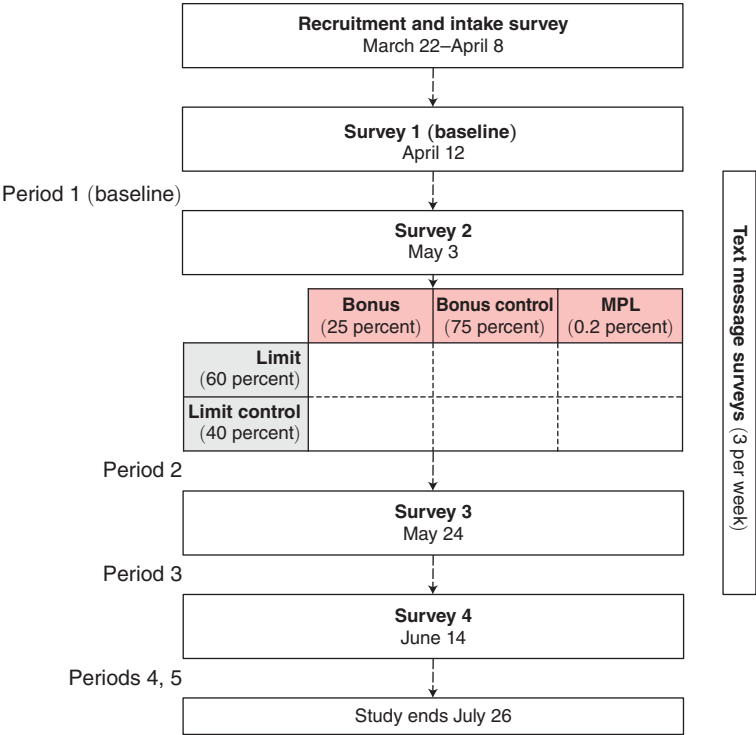


FIGURE 2. EXPERIMENTAL DESIGN

II. Experimental Design

A. Overview

Our experiment is designed to provide direct evidence on the magnitude of habit formation, perceived habit formation, temptation, and perceived temptation, as well as to identify the remaining key parameters of the quadratic model. The experiment ran from March 22 to July 26, 2020, with participants completing an intake questionnaire and four surveys. Figure 2 summarizes the experimental design, and Table 1 presents sample sizes at each step.

Between March 22 and April 8, we recruited participants using Facebook and Instagram ads. Online Appendix Figure A1 presents the ads. To minimize sample selection bias, the ads did not hint at our research questions or suggest that the study was related to smartphone use or social media. Of 3,271,165 unique users who were shown one of the ads, 26,101 clicked on it. This 0.8 percent click-through rate is close to the average click-through rate on Facebook ads (Irvine 2018).

Clicking on the ad took the participant to a brief screening survey, which included several background questions, the consent form, and instructions on how to install Phone Dashboard. To be eligible, participants had to be a US resident between 18 and 64 years old, use an Android as their primary phone, and use only one smartphone regularly. These criteria were satisfied by 18,589 people, of whom 8,514

TABLE 1—EXPERIMENT TIMELINE AND SAMPLE SIZES

Phase	Date	Sample size
Recruitment and intake	March 22–April 8	3,271,165 shown ads 26,101 clicked on ads 18,589 passed screen 8,514 consented 5,320 finished intake survey
Survey 1 (baseline)	April 12	4,134 began survey 1 4,038 finished survey 1 2,126 were randomized
Survey 2	May 3	2,068 began survey 2 2,053 informed of treatment, of which 2,048 were not in MPL group 2,032 finished survey 2
Survey 3	May 24	1,993 began survey 3 1,981 finished survey 3
Survey 4	June 14	1,954 began survey 4 1,948 finished survey 4
Completion	July 26	1,938 kept Phone Dashboard through July 26, of which 1,933 were not in MPL group (“analysis sample”)

consented to participate in the study. Of these, 5,320 successfully installed Phone Dashboard and finished the intake survey.

Surveys 1–4 were administered on Sundays at three-week intervals between April 12 and June 14. We define  $t = 1, 2, 3, \dots$  to be the three-week periods beginning Monday April 13, so period  $t$  is the three weeks immediately after survey  $t$ . For our data analysis and interventions, we want to exclude survey days, so all periods are 20 days long, from a Monday to a Saturday. Survey 1 recorded participant demographics. We describe the other survey content below.

As illustrated in Figure 2, we randomized participants into bonus and limit treatment conditions (detailed below) using a factorial design. We randomized participants to the bonus, bonus control, or the MPL group with 25, 75, and 0.2 percent probability, respectively. We independently randomized participants to the limit or limit control groups with 60 and 40 percent probability, respectively. We refer to the intersection of the bonus control and limit control groups as the control group. We balanced the randomization within eight strata defined by above-versus below-median baseline FITSBY use, *restriction index*, and *addiction index* (described below). The treatments began on survey 2.

All participants received \$5 for completing the baseline survey and \$25 if they completed the remaining surveys and kept Phone Dashboard installed through July 26. Participants were also entered in a drawing for a \$500 gift card, in which two winners were drawn.

As shown in Table 1, 4,038 participants completed survey 1. We dropped 1,912 of these participants from the experiment after survey 1 because they reported that

they already used another app to limit their phone use (5 percent of the sample) or failed data quality checks.<sup>13</sup> The remaining 2,126 participants were invited to take survey 2, of whom 2,053 opened the survey and reached the point where the treatments began. Of those, 1,938 completed the study—remarkably low attrition for a 12-week study with multiple surveys.

In addition to back-loading the survey payments, several other factors contributed to our limited attrition. There were two surveys (the intake and survey 1) before the treatments began, inducing likely attriters to attrit beforehand. At the beginning of survey 2, just before the treatments began, we informed people that “anyone who drops out after this page can really damage the entire study,” and offered them a choice to drop out at that moment or commit to finishing the whole study. For participants who had not yet completed each of surveys 2–4, we sent daily reminders for six days after the survey had been fielded, and after four days we began offering an additional payment for completing all remaining surveys. We also sent reminder emails to people who had failed to respond to two consecutive text messages.

### B. Phone Dashboard

Phone Dashboard is an Android app that was developed by a company called Audacious Software for our experiment. Online Appendix Figure A2 presents screenshots. Our experiment includes only Android users because a similar functionality cannot be implemented by third-party apps on iOS.

Phone Dashboard records the app that is in the foreground of a smartphone every five seconds when the screen is on; we use these data to construct our measure of consumption. It does not record the content that the user is viewing within the app. Users can see their cumulative screen time by day and by week on the Phone Dashboard home screen. This usage information was designed to be particularly useful for participants in the bonus and limit groups who might want to track their usage, but the control group also used the app: the bonus, limit, and control groups used Phone Dashboard for an average of 1.4, 1.5, and 1.0 minutes per day during periods 2–5.

### C. Bonus Treatment

The bonus treatment was designed to identify projection bias (the parameter  $\alpha$ ), actual habit formation ( $\rho$  and  $\zeta$ ), and the curvature of utility ( $\eta$ ). To facilitate the MPL described below, survey 2 explained the bonus to all participants before telling them whether they were selected to receive it and when it would be in force. Participants were told, “If you’re selected for the Screen Time Bonus, you would receive \$50 for every hour you reduce your average daily FITSBY screen time below a Bonus Benchmark of [X] hours per day over the 3-week period, up to \$150.”

<sup>13</sup> Participants failed data quality checks if they (i) did not promise to “provide my best answers” on our surveys, (ii) reported having idiosyncratic bugs with Phone Dashboard, (iii) failed to answer more than two of our text message questions between survey 1 and survey 2, (iv) had a device that was incompatible with Phone Dashboard, or (v) were missing screen time data during the baseline period.

The survey then gave several examples, including:

- “If you reduce your FITSBY screen time to  $\$[X-1]$  hours and 30 minutes per day over the next 3 weeks, you would receive \$25.”
- “If your FITSBY screen time is above  $\$X$  hours per day, you would receive \$0.”

We set the bonus benchmark  $[X]$  as the participant’s average FITSBY hours per day from period 1, rounded up to the nearest integer.

After the MPL described below, the bonus group was informed that they had been randomly selected to receive the bonus for screen time reductions during period 3—i.e., starting in three weeks. The bonus control group was informed that they would not receive the bonus. To ensure that participants understood, each participant had to answer a question by correctly indicating their bonus treatment condition before advancing. We also sent three text messages reminders to the bonus group during period 2, which read “Don’t forget, we’ll pay you \$50 for every hour you reduce your average daily screen time between May 24 and June 14. There is no bonus for changing your screen time before then.” People were asked to respond to the text message to confirm that they had read it. Survey 3 included an additional reminder for the bonus treatment group. While we received substantial feedback on the surveys and many emails from our 2,000 participants during the study and our earlier pilots, none of these interactions suggested confusion about the timing of the bonus.

The bonus group’s anticipatory response to the bonus in period 2 (before the incentive was in effect) provides information about the magnitude of projection bias  $\alpha$ . The contemporaneous response in period 3 (while the incentive was in effect) provides information about the price response parameter  $\eta$ . The long-term effects in periods 4 and 5 (after the incentive had ended) provide information about the magnitude and decay of habit ( $\zeta$  and  $\rho$ ).

#### D. *Limit Treatment*

The limit treatment was designed to understand self-control problems and help identify the temptation parameter  $\gamma$ . The limit treatment group was given access to functionality in Phone Dashboard that allows users to set daily time limits for each app on their phone; see online Appendix Figure A2 for screenshots. Any changes to the limits take effect the next day. Phone Dashboard serves five-minute and one-minute push notifications as an app’s daily time limit approaches. When the limit arrives, users can “snooze” their limit and get an additional amount of time that they specify—but starting only after a delay. Within the limit group, we randomly assigned participants with equal probability to delays of 0, 2, 5, or 20 minutes or a condition where the ability to snooze was disabled. To keep the scope of this paper manageable, we focus only on the comparison between the limit and limit control groups; we plan to study the variation in snooze delays in a separate paper. To reduce attrition and uninstallation, Phone Dashboard also allows people to permanently opt out of the limits; about 4 percent of the limit group did so.

The limit group was first given access to the Phone Dashboard limit functionality on survey 2, after the Screen Time Bonus MPL described below, and they retained

access to the feature for the duration of the experiment. To introduce the limits, we first gave participants instructions on how to set daily app usage limits for themselves. The survey then asked participants what time limits they would like to set for themselves on each FITSBY app over the next three weeks. We then asked participants to update their Phone Dashboard app, which activated the limit functionality, and encouraged them to set the limits they had reported a moment earlier. The limit control group was never told about limits and continued to have a version of Phone Dashboard that did not have the limit functionality.

In the analysis below, we interpret use of the limits as evidence of perceived self-control problems ( $\tilde{\gamma} > 0$ ).

### *E. Bonus and Limit Valuations*

We used incentive-compatible MPL mechanisms to elicit valuations of the Screen Time Bonus and the limit functionality. Because both the bonus and the limit functionality reduce future social media use, these valuations help identify perceived temptation  $\tilde{\gamma}$ .

All MPLs included a table with a series of choices between “option A” and “option B” in separate rows. Option B was the same in each row, while option A included an amount of money that decreased monotonically from top to bottom. Participants would typically choose option A at the top and option B at the bottom, and we infer their valuation of option B from the row where they switch. To encourage valid answers, participants who did not switch between option A and option B exactly once were alerted to this fact and given a chance to change their answers. All MPLs were incentivized, as described below. To help participants become familiar with MPLs, survey 1 included an incentivized practice MPL that asked participants to choose between receiving different survey completion payments at different times.

Our approach to valuing the Screen Time Bonus builds on Allcott et al. (2022) and Carrera et al. (2021). Survey 2 informed participants of their average daily FITSBY screen time over the past three weeks and asked them to predict their screen time over the next three weeks. The survey then introduced the Screen Time Bonus and asked participants to predict how much they would reduce their FITSBY screen time relative to their original prediction if they were selected for the bonus.

After these two predictions, we asked participants to make a hypothetical choice between the Screen Time Bonus and a payment equal to their expected earnings from the bonus. The survey described potential considerations as follows:

- “You might prefer \$[expected earnings] instead of the Screen Time Bonus if you don’t want any pressure to reduce your screen time.”
- “You might prefer the Screen Time Bonus instead of \$[expected earnings] if you want to give yourself extra incentive to use your phone less.”

Participants then completed an MPL where Option B was receiving the Screen Time Bonus, and Option A was receiving a payment ranging from \$150 to \$0.

To make the MPL incentive compatible, participants were told, “Last week, the computer randomly selected some participants to receive what they choose on the

multiple price list below, and also randomly selected one of the rows to be ‘the question that counts.’ If you were randomly selected to participate, you will be paid based on what you choose in that row.” 0.2 percent of participants were randomly assigned to the MPL group that received what they chose on a randomly selected row.

On survey 3, the limit group completed an MPL that elicited valuations of the Phone Dashboard limit functions. Option B was retaining access to the Phone Dashboard limit functions, and Option A was having those functions disabled for the following three weeks in exchange for a dollar payment that ranged from \$20 to -\$1. The MPL group received what they chose on a randomly selected row.

### F. *Predicted Use*

At the end of surveys 2, 3, and 4, we elicited predictions of future FITSBY use. These predictions help identify the degree of naïveté or sophistication about temptation—the difference between  $\gamma$  and  $\tilde{\gamma}$ .

Before each elicitation, we told each participant their average FITSBY screen time over the previous three weeks. Surveys 2 and 3 also reminded the bonus and limit groups about the bonus and limits. Survey 2 then elicited predictions of FITSBY screen time for the next three weeks (period 2), the three weeks after that (period 3), and the three weeks after that (period 4). Survey 3 elicited separate predictions for periods 3, 4, and 5. Survey 4 elicited separate predictions for periods 4 and 5.

Predictions were incentivized. Survey 2 told participants, “Answer carefully, because you might earn a Prediction Reward. After the study ends, we will pick a prediction question at random and check how close your prediction is. If your predicted daily screen time is within 15 minutes of your actual screen time, we will pay you an additional \$X.” We randomized the prediction reward X to be \$1 or \$5, each with 50 percent probability.

### G. *Survey Outcome Variables*

Surveys 1, 3, and 4 asked questions designed to measure participants’ perceptions of their addiction and SWB. For the nine weeks between survey 1 and survey 4, we also sent three text messages per week with a subset of questions that we thought were important to ask in real time instead of retrospectively. Using these questions, we construct five prespecified outcome variables. Online Appendix A.1 presents details on the survey questions.

*Ideal Use Change.*—The survey said, “Some people say they use their smart-phone too much and ideally would use it less. Other people are happy with their usage or would ideally use it more. How do you feel about your smartphone use over the past 3 weeks?”

- “I use my smartphone too much.”
- “I use my smartphone the right amount.”
- “I use my smartphone too little.”



For people who said they used their smartphone “too much” or “too little,” we then asked, “Relative to your actual use over the past 3 weeks, by how much would you ideally have [reduced/increased] your smartphone use?” The *ideal use change* variable is the answer to this question, in percent.

*Addiction Scale.*—Our addiction scale is a battery of 16 questions modified from two well-established survey scales, the Mobile Phone Problem Use Scale (Bianchi and Phillips 2005) and the Bergen Facebook Addiction Scale (Andreassen et al. 2012). The questions attempt to measure the six core components of addiction identified in the addiction literature: salience, tolerance, mood modification, relapse, withdrawal, and conflict (Griffiths 2005).

The survey asked, “In the past three weeks, how often have you ...,” with a matrix of 16 questions, such as:

- “used your phone longer than intended?”
- “felt anxious when you don’t have your phone?”
- “lost sleep due to using your phone late at night?”

Possible answers were never, rarely, sometimes, often, and always, which we coded as 0, 0.25, 0.5, 0.75, and 1, respectively. *Addiction scale* is the sum of these numerical scores for the 16 questions.

*SMS Addiction Scale.*—The SMS addiction scale includes shortened versions of nine questions from the addiction scale. Examples include:

- “In the past day, did you feel like you had an easy time controlling your screen time?”
- “In the past day, did you use your phone mindlessly?”
- “When you woke up today, did you immediately check social media, text messages, or email?”

People were instructed to text back their answers on a scale from 1 (not at all) to 10 (definitely). *SMS addiction scale* is the sum of these scores for the nine questions.

*Phone Makes Life Better.*—The survey asked, “To what extent do you think your smartphone use makes your life better or worse?” Responses were on a scale from −5 (“Makes my life worse”) through 0 (“Neutral”) to +5 (“Makes my life better”).

*Subjective Well-Being.*—We use standard measures from the SWB literature, mostly following the measures from our own earlier work (Allcott et al. 2020). The survey asked, “Please tell us the extent to which you agree or disagree with each of the following statements. **Over the last three weeks,**” with a matrix of seven questions:

- “... I was a happy person.”
- “... I was satisfied with my life.”
- “... I felt anxious.”

- "... I felt depressed."
- "... I could concentrate on what I was doing."
- "... I was easily distracted."
- "... I slept well."

Possible answers were on a seven-point scale from "strongly disagree" through "neutral" to "strongly agree," which were coded as  $-1$ ,  $-2/3$ ,  $-1/3$ ,  $0$ ,  $1/3$ ,  $2/3$ , and  $1$ , respectively. The variable *SWB* is the sum of these numerical scores for the seven questions, after reversing *anxious*, *depressed*, and *easily distracted* so that more positive reflects better SWB.

*Indices.*—We define the *survey index* to be the sum of the five survey outcome variables described above, weighted by the baseline inverse covariance matrix as described by Anderson (2008). When presenting results and constructing this index, we orient the variables so that more positive values imply normatively better outcomes. Thus, we multiply *addiction scale* and *SMS addiction scale* by  $(-1)$ .

We define the *restriction index* to be the sum of *interest in limits* (with the four categorical answers coded as  $0$ ,  $1$ ,  $2$ , and  $3$ ) and *ideal use change*, after normalizing each into standard deviation units. We define the *addiction index* to be the sum of *addiction scale* and *phone makes life better* after normalizing each into standard deviation units. We use these two indices for stratified randomization and as moderators when testing for heterogeneous treatment effects.

#### H. Preanalysis Plan

We submitted our preanalysis plan (PAP) on May 4, the day that posttreatment data collection began. The PAP specified (i) the equation for treatment effect estimation (equation (4) below); (ii) the construction of the survey outcome variables and indices described in Section IIG, the *limit tightness* variable, and the win-sORIZATION of predicted FITSBY use; and (iii) the analysis of heterogeneous treatment effects by splitting the sample on above- versus below-median values of six moderators: education, age, gender, baseline FITSBY use, *restriction index*, and *addiction index*. The PAP also included shells of Tables 1, 2, and online Appendix Tables A1–A3, as well as Figures 1–6, online Appendix Figures A1–A4, A8, and A28–A34.

We deviate from the PAP in five ways. First, the bottom left panel of Figure 3 includes results from each addiction scale question, whereas the PAP figure shell presented the sum across all questions. Second, we clarify that our analysis sample includes only the balanced panel of people who completed the study. Results are essentially identical if we use an unbalanced panel that includes data from attriters before they attritted, but the balanced panel is helpful in ensuring that our habit formation results are not spuriously driven by attrition. Third, three figures from the PAP are not included here, as we plan to study them in a separate paper. Fourth, Figure 6 includes predicted FITSBY use from all surveys before period  $t$ , whereas the PAP figure shell presented predictions from only the survey immediately before period  $t$ . Fifth, we use equation (4) for subgroup analysis, whereas the PAP specified that we would use an instrumental variables regression. We present the prespecified

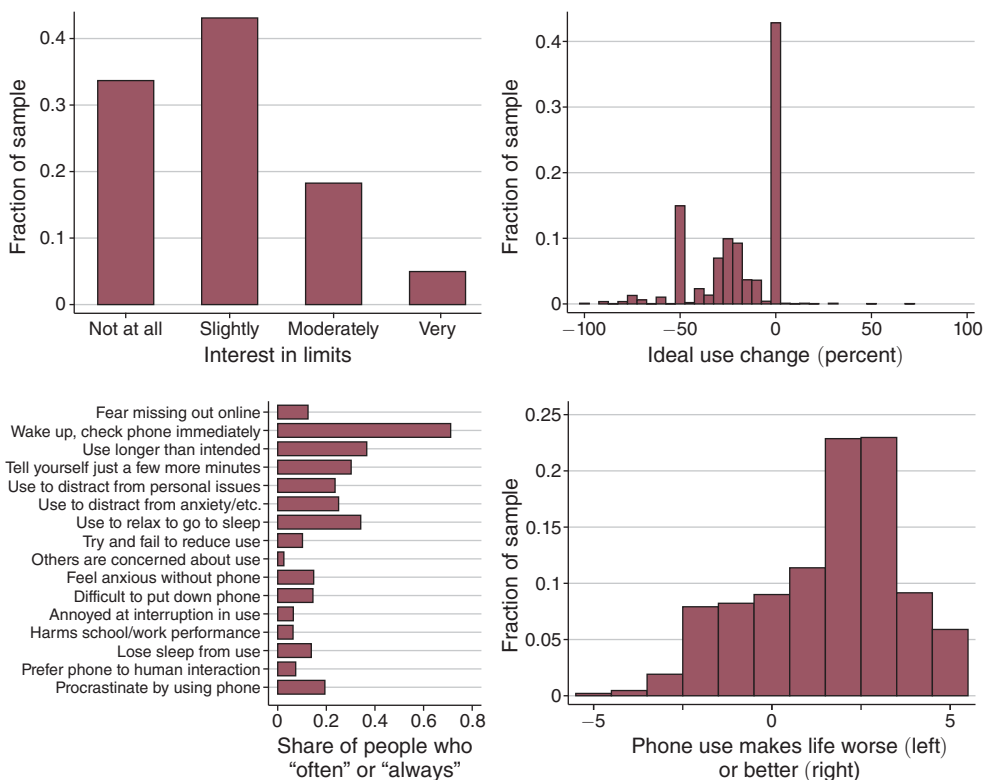


FIGURE 3. BASELINE QUALITATIVE EVIDENCE OF SELF-CONTROL PROBLEMS

*Notes:* This figure presents the distributions of four measures of smartphone addiction from the baseline survey. *Interest in limits* is the answer to, “How interested are you to set limits on your phone use?” *Ideal use change* is the answer to, “Relative to your actual use over the past 3 weeks, by how much would you ideally have [reduced/increased] your screen time?” The bottom left panel presents the share of participants who responded “often” or “always” to each of 16 questions modified from the Mobile Phone Problem Use Scale and the Bergen Facebook Addiction Scale. *Phone use makes life worse or better* is the answer to, “To what extent do you think your smartphone use made your life better or worse over the past 3 weeks?”

instrumental variables estimates in online Appendix D.4. The results are similar, and we decided that equation (4) was simpler.

### III. Data

The analysis sample for all results reported below is the balanced panel of 1,933 participants who were assigned to either bonus or bonus control (not the MPL group), completed all four surveys, and kept Phone Dashboard installed until the end of the study on July 26. This group’s attrition rate after being informed of treatment was  $(1 - 1,933/2,048) \times 100$  percent  $\approx 5.6$  percent. Attrition rates and observable characteristics are balanced across the bonus and limit treatment conditions; see online Appendix Tables A1 and A2.

TABLE 2—SAMPLE DEMOGRAPHICS

	Analysis sample (1)	US adults (2)
Income (\$000s)	40.8	43.0
College	0.67	0.30
Male	0.39	0.49
White	0.72	0.74
Age	33.7	47.6
Period 1 phone use (minutes/day)	333.0	.
Period 1 FITSBY use (minutes/day)	152.8	.

*Note:* Column 1 presents average demographics for our analysis sample, and column 2 presents average demographics of American adults using data from the 2018 American Community Survey.

Table 2 quantifies the representativeness of our analysis sample on observables, by comparing their demographics to the US adult population. Our sample is more educated, more heavily female, younger, and slightly lower income than the US population. We estimate an alternative specification of our structural model with sample weights to adjust for these observable differences.

Table 2 also shows that the average participant had 333 minutes per day of screen time during the baseline period, of which 153 minutes (46 percent) was on FITSBY apps. Different sources report very different estimates of average social media use and smartphone screen time for US adults, so we do not report nationwide averages in the table. Kemp (2020) reports that internet users in the United States and worldwide, respectively, spend an average of 123 and 144 minutes per day on social media, mostly on mobile devices. Wurmser (2020) and Brown (2019) report national averages of 186 and 324 minutes of total smartphone screen time per day, respectively. The comparisons suggest that the heavy use in our sample may not be far from the national average.

During the baseline period, the average participant used Facebook, browsers, YouTube, Instagram, Snapchat, and Twitter for 69, 44, 23, 24, 15, and 15 minutes per day, respectively; see online Appendix Figure A3. Online Appendix Figure A4 presents the distribution of baseline FITSBY use. Online Appendix Table A3 presents descriptive statistics for the survey outcome variables.

IV. Model-Free Results

A. Treatment Effect Estimating Equation

To estimate treatment effects, define  $Y_{it}$  as an outcome for participant  $i$  for period  $t$ . The variable  $Y_{it}$  could represent a survey outcome variable measured on survey  $t \in \{3, 4\}$ , or period  $t$  FITSBY use. Define  $L_t$  and  $B_t$  as limit and bonus group indicators. Define  $\mathbf{X}_{i1}$  as a vector of baseline covariates: baseline FITSBY use and, if and only if  $Y$  is a survey outcome variable, the baseline value  $Y_{i1}$  and the baseline value of *survey index*. Define  $\nu_{it}$  as a vector of the eight randomization stratum indicators,

allowing separate coefficients for each period  $t$ . We estimate the effects of the limit and bonus treatments using the following regression:

$$(4) \quad Y_{it} = \tau_t^B B_i + \tau_t^L L_i + \beta_t \mathbf{X}_{it} + \nu_{it} + \varepsilon_{it}.$$

When combining data across multiple periods, we cluster standard errors by participant.

### B. Baseline Qualitative Evidence

Figure 3 presents qualitative evidence on digital addiction from the baseline survey. The top two panels present the variables in the *restriction index*. The top left panel shows that 23 percent of people reported being “moderately” or “very” interested in setting time use limits on their smartphone apps, while 34 percent reported being “not at all” interested. The top right panel presents the distribution of responses to the *ideal use change* question. 42 percent of people said that they used their smartphone the right amount over the past three weeks, and only 0.5 percent said that they used it too little. Among people who said they used their smartphone too much, the average ideal reduction was 34 percent.

Survey 1 also asked people to report their ideal use change for specific apps or categories. FITSBY, games, video streaming, and messaging are the nine apps on which people want to reduce screen time the most; see online Appendix Figure A8. Facebook is by far the most tempting app: the average participant would ideally reduce Facebook use by 22 percent. The average participant did not want to change their use of email, news, and maps and wanted to slightly increase use of phone, music, and podcast apps.

The bottom two panels present the variables in the *addiction index*. The bottom left panel presents the share of participants who responded “often” or “always” on each question in the *addiction scale*. The top seven questions capture three components of moderate addictions (salience, tolerance, and mood modification); 33 percent of participants often or always experience each of these, and 84 percent often or always experience at least one. The bottom nine questions capture three components of more severe addictions (relapse, withdrawal, or conflict); 11 percent of participants often or always experience each of these, and 41 percent often or always experience at least one. The bottom right panel shows that while most people think that their smartphone use makes their life better, 19 percent think that it makes their life worse. Taken together, these results suggest substantial heterogeneity: many people report experiences consistent with addiction, while many others do not.

Our experiment took place during the COVID-19 pandemic, which significantly disrupted people’s daily routines. To understand how this might affect our results, we included several baseline survey questions, which we report in online Appendix C. We saw that 78 percent of people reported having more free time as a result of the pandemic, and 88 percent of people reported that the pandemic had increased their phone use. However, it is not clear that the pandemic affected the extent of self-control problems: the means and distributions of key qualitative measures of addiction that we also asked for 2019, *ideal use change* and *phone makes life better*, were statistically different but economically similar. *Ideal use change* is

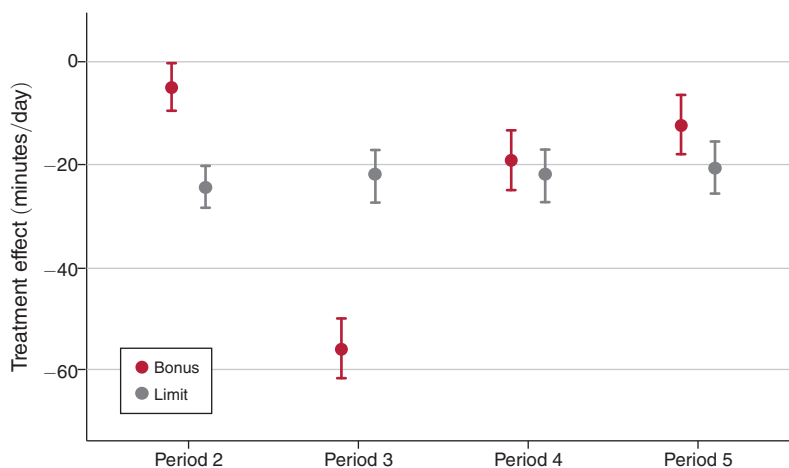


FIGURE 4. TREATMENT EFFECTS ON FITSBY USE

Notes: This figure presents effects of the bonus and limit treatments on FITSBY use using equation (4). FITSBY use refers to screen time on Facebook, Instagram, Twitter, Snapchat, browsers, and YouTube.

closer to zero in 2020 compared to in 2019, suggesting less perceived self-control problems, but *phone makes life better* is also less positive, suggesting more perceived self-control problems.

### C. Bonus Treatment and Habit Formation

The darker coefficients in Figure 4 present the effect of the bonus on FITSBY use, estimated using equation (4). Recall that the bonus provides an incentive to reduce FITSBY use in period 3, but we informed participants about whether or not they were offered the bonus at the beginning of period 2. The incentive is \$50 per *average* hour measured over the 20-day period, or \$2.50 per hour of consumption.

In period 3 (while the incentive was in effect), the bonus group reduced FITSBY use by 56 minutes per day, or 39 percent relative to the Control group. This is a striking price response: it implies that participants value a substantial share of smartphone FITSBY use at less than \$2.50 per hour.

In periods 4 and 5 (after the incentive had ended), the bonus group still reduced FITSBY use by 19 and 12 minutes per day, respectively. This persistent effect suggests substantial habit formation, implying  $\zeta > 0$  in our model. The decay of the effect in period 5 relative to period 4 provides information about the habit stock decay parameter  $\rho$  in our model.

In period 2 (before the incentive was in effect), the bonus group reduced FITSBY use by 5.1 minutes per day, which is marginally statistically significant. This is consistent with the model's prediction that a consumer who perceives habit formation should reduce period 2 consumption in order to reduce period 3 marginal utility, which makes it easier to reduce period 3 consumption in response to the financial incentive. However, additional evidence suggests some caution about interpreting the period 2 effect as forward-looking habit formation. Online Appendix Figures A9 and A10 break out the period 2 effect separately by day and week, showing that it



loads mostly on the first half of the period. If anything, forward-looking habit formation would predict the opposite pattern, with larger anticipatory effects closer to the beginning of the incentive period. Possible explanations include intertemporal substitution, a temporary idiosyncratic effect, and the salience of the bonus after its introduction on survey 2.<sup>14</sup>

#### D. Limit Treatment and Temptation

The limit group made extensive use of the limit functionality. To summarize the stringency of time limits, we define the variable *limit tightness* to be the amount by which a user's limits would have hypothetically reduced screen time if applied to their baseline use.<sup>15</sup> *Limit tightness* equals zero (instead of missing) for an app if the participant doesn't have the app or doesn't set a limit, so this variable speaks to what apps contribute the most to aggregate temptation. About 89 percent of the limit group had positive *limit tightness* at some point during the experiment, suggesting that they set binding screen time limits, and 78 had positive *limit tightness* in period 5, meaning that they kept those limits for more than three weeks after the final survey. Participants most wanted to restrict Facebook, web browsers, YouTube, and Instagram: *limit tightness* averaged 20, 10, 8, and 6 minutes per day on those apps, respectively, across periods 2–5. Across all apps, the limit group's average *limit tightness* was 53 minutes per day. See online Appendix Figures A11 and A12 for details.

The lighter coefficients on Figure 4 present the effect of the limit on FITSBY use. These actual effects are smaller than the *limit tightness* values in the previous paragraph primarily because users snooze the limits. Access to the limit functionality reduced use in periods 2–5 by an average of 22 minutes per day, or 16 percent relative to the control group. The effects attenuate only slightly as the experiment continues, and the effect is still 19 minutes per day in the last week of period 5. This is notable because while surveys 2 and 3 walked people through a limit-setting process and survey 4 included an optional review of the limits, the end of period 5 is nine weeks after survey 3 and six weeks after survey 4. These continuing effects suggest that while motivation might decrease over time, use of the limits is not primarily driven by confusion or temporary novelty. Furthermore, online Appendix D.1 shows that *limit tightness* is correlated in expected ways with bonus and limit valuations

<sup>14</sup> Although we stratified randomization on period 1 FITSBY use and also control for period 1 use when estimating equation (4), some idiosyncratic factor could temporarily affect consumption in bonus versus bonus control at the beginning of period 2. Some evidence supports this possibility: online Appendix Figure A9 shows that consumption is slightly lower in the bonus group compared to bonus control in the final 11 days of period 1. Salience could also play a role, although as described in Section IIC, we took many steps to eliminate confusion about the timing of the bonus incentive period, and participants likely would have emailed our team if they were confused.

<sup>15</sup> Specifically, define  $x_{iad}$  as the screen time of person  $i$  on app  $a$  on day  $d$  in period  $t$ . Define  $h_{iat}$  as the average screen time limit in place in period  $t$ , and define  $N_{d \in t=1}$  as the number of days in the baseline period. *Limit tightness* is

$$(5) \quad H_{iat} = \frac{1}{N_{d \in t=1}} \sum_{d \in t=1} \max\{0, x_{iad} - h_{iat}\}.$$

If the daily limit  $h_{iat}$  would not have been binding in baseline day  $d$ , the max function returns 0. If  $h_{iat}$  would have been binding in day  $d$ , then the max function returns the excess screen time on that day. We aggregate over apps to construct user-level limit tightness  $H_{it} = \sum_a H_{iat}$ .

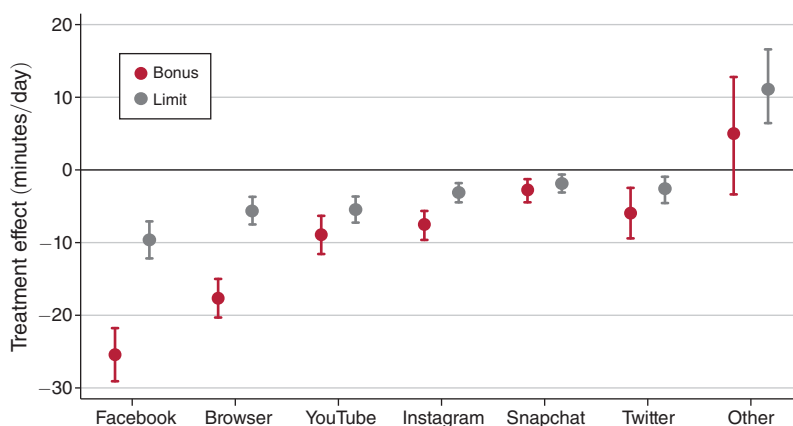


FIGURE 5. EFFECTS ON SMARTPHONE USE BY APP

*Notes:* This figure presents effects of the bonus and limit treatments on smartphone use by app using equation (4). The bonus effects are measured in period 3, while the limit effects are measured in periods 2–5. FITSBY use refers to screen time on Facebook, Instagram, Twitter, Snapchat, browsers, and YouTube. FITSBY apps are in order of decreasing period 1 use.

and with survey measures of addiction and desire to reduce screen time. This evidence consistently points toward perceived self-control problems, implying  $\tilde{\gamma} > 0$  in our model.

When we add the interaction between bonus and limit group indicators to equation (4), the main effects are similar and the interaction terms are not statistically significant; see online Appendix Figure A13.

### E. Substitution

Figure 5 presents usage effects of the bonus (in period 3 only) and the limit (across periods 2–5) separately by app. Among the FITSBY apps, Facebook sees the largest reductions, followed by web browsers, YouTube, Instagram, Twitter, and Snapchat. The effects on other apps (the rightmost coefficients) provide evidence on the extent to which participants substituted FITSBY time to alternative apps. The bonus has no statistically detectable effect on use of other apps in period 3, and the confidence intervals rule out any substantial substitution relative to the 56 minutes per day reduction in FITSBY use. The limit induces substitution of 12 minutes per day, so that roughly one-half of the FITSBY screen time that the limit eliminates moves to other apps where people had been less likely to set limits.

One important limitation is that we cannot directly monitor FITSBY use on devices other than the participant's smartphone. We screened out potential participants who reported using more than one smartphone regularly, but our remaining participants may still have used desktops, tablets, or other devices. To provide some evidence on this substitution, survey 4 asked participants to estimate their FITSBY use on other devices in period 3 compared to the three weeks before they joined the study. The results, shown in online Appendix Figure A14, imply that the limit increased FITSBY use on other devices by a marginally significant 4.2 minutes per

day. The bonus *reduced* the amount of time they spent on FITSBY on other devices by 8.1 minutes per day, suggesting that time on other devices was a mild complement in this case.

The differences in substitution induced by the bonus versus limit are notable. In a simple model where other apps and devices are either complements or substitutes for smartphone FITSBY use, the substitution effects described above might have the same sign for both the bonus and limit and might be in proportion to their direct effects on smartphone FITSBY use. In contrast, a much smaller share of the effect on FITSBY use is substituted to other smartphone apps for the bonus compared to the limit, and the self-reported effects on FITSBY use on other devices have opposite signs for the bonus versus the limit. This is an interesting result to understand in future work.

#### F. Predicted versus Actual Use

Figure 6 presents predicted and actual FITSBY use in the control condition, where participants had neither the bonus nor the limit functionality. As specified in our PAP, we winsorize predicted use at no more than 60 minutes per day more or less than actual use in the corresponding period. Within each period, the leftmost spike is actual average use. The spikes to the right are average predictions. The point estimates show that people consistently underestimate their use in all future periods, even though actual use is fairly stable throughout the experiment and the surveys had reminded them of their past use before eliciting predictions. This is consistent with naïveté, implying  $\tilde{\gamma} < \gamma$  in our model.

Figure 7 presents predicted versus actual habit formation. Within each period, the leftmost point is the treatment effect of the bonus on actual use, reproduced from Figure 4. Recall that before the MPL for the Screen Time Bonus on survey 2, we asked people to report the percent by which they thought the bonus would reduce their FITSBY use. Their estimates (translated into minutes using their status quo predictions) are almost exactly correct on average: 52 minutes per day. Then on survey 3, we asked people to predict their use in future periods. Figure 7 also presents treatment effects of the bonus on predicted use, estimated from equation (4). The figure shows that people correctly predict that the bonus will reduce their consumption in period 3 and that this reduction will persist even after the incentive is no longer in effect. If anything, comparing the time path of actual versus predicted effects suggests that people overestimate the extent of habit formation. Overall, these results suggest that people are well aware of habit formation.

Online Appendix D.1 presents additional results that validate that the usage predictions are meaningful. Predicted use lines up well with actual use, and the higher (\$5 instead of \$1) prediction accuracy reward slightly reduces the absolute value of the prediction error but has tightly estimated zero effects on predicted use, actual use, and the level of the prediction error.

#### G. Bonus and Limit Valuations

On the survey 3 MPL, the average limit group participant was willing to give up a \$4.20 fixed payment for three weeks of access to the limit functionality. About 58

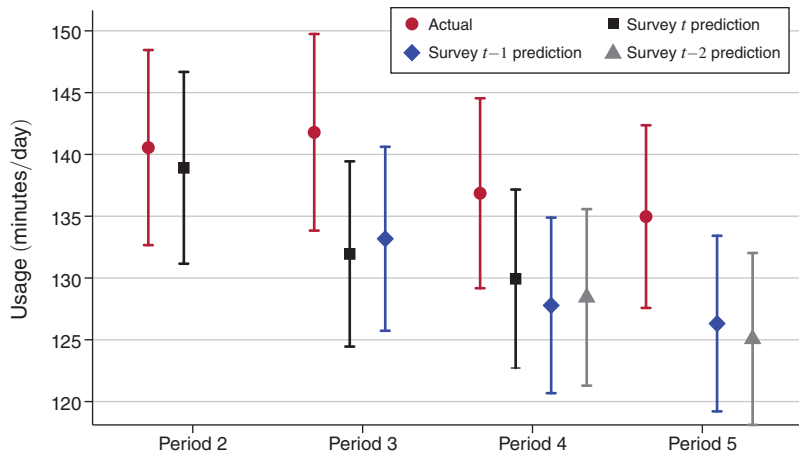


FIGURE 6. PREDICTED VERSUS ACTUAL FITSBY USE IN CONTROL CONDITIONS

*Notes:* This figure presents average actual FITSBY use by period and average predicted FITSBY use for that period, for participants in the intersection of the bonus control and limit control groups. Period  $t$  is the three weeks immediately after survey  $t$ , so “survey  $t$  prediction” is the prediction for period  $t$  made just prior to period  $t$ . FITSBY use refers to screen time on Facebook, Instagram, Twitter, Snapchat, browsers, and YouTube.

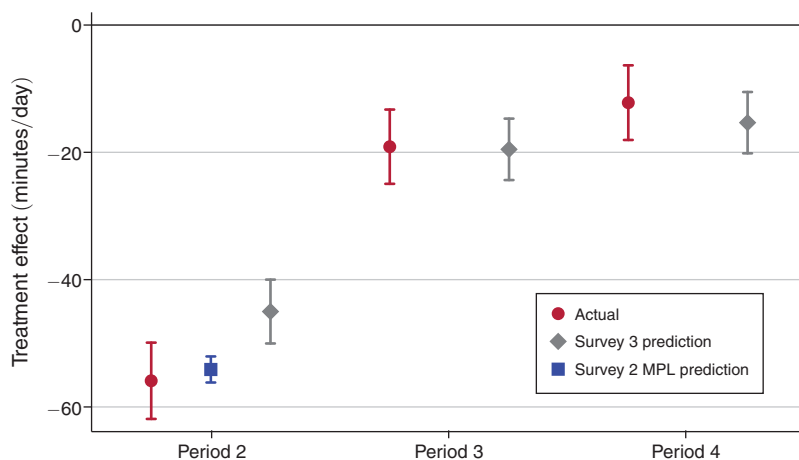


FIGURE 7. PREDICTED VERSUS ACTUAL HABIT FORMATION

*Notes:* This figure presents the treatment effects of the bonus on FITSBY use and on predicted FITSBY use from survey 3 using equation (4), as well as the average predicted bonus treatment effect elicited on survey 2 before the bonus multiple price list (MPL). FITSBY use refers to screen time on Facebook, Instagram, Twitter, Snapchat, browsers, and YouTube.

percent of participants were willing to give up at least some money for the limits, and 20 percent were willing to give up more than \$10; see online Appendix Figure A17. This willingness to pay for a commitment device is consistent with perceived self-control problems ( $\tilde{\gamma} > 0$ ) and unmet market demand for digital self-control tools.

On the survey 2 MPL, people who perceive self-control problems should prefer the Screen Time Bonus over higher fixed payments, as the incentive helps bring

future use in line with current preferences. We show in online Appendix E.5 that participants' average valuation of the bonus is consistent with perceived self-control problems ( $\tilde{\gamma} > 0$ ).

Online Appendix D.1 presents additional results that validate that the MPL responses are meaningful. First, participants' valuations of the bonus are correlated with the amount of money they could expect to earn. Second, the bonus and limit valuations are correlated with each other and with *limit tightness*, *ideal use change*, *addiction scale*, *SMS addiction scale*, and other variables in expected ways. Third, after the bonus MPL, we asked people to "select the statement that best describes your thinking when trading off the Screen Time Bonus against the fixed payment." 24 percent responded that "I wanted to give myself an incentive to use my phone less over the next three weeks, even though it might result in a smaller payment," and this group had a higher average valuation.

#### H. Effects on Survey Outcomes

Figure 8 presents the effects of the bonus and limit treatments on the survey outcomes described in Section IIG. The outcome variables are signed so more positive effects always correspond to less addiction and/or higher SWB. Following our PAP, when estimating effects on survey outcomes, we constrain the limit effect to be the same for surveys 3 and 4 (because we correctly anticipated similar "first stage" effects on FITSBY use in both periods 2 and 3) and we report the bonus effect only for survey 4 (because we correctly anticipated negligible "first stage" effects on FITSBY use in period 2).<sup>16</sup>

Figure 8 shows that both interventions significantly reduced self-reported measures of addiction. Online Appendix Table A6 presents coefficient estimates and *p*-values. The bonus effect is larger than the limit effect for five of the six variables, consistent with the bonus's larger effects on FITSBY use. The bonus decreased *ideal use change* by 0.41 standard deviations (about 9 percentage points), while the limit decreased it by 0.23 standard deviations (about 5 percentage points). Both interventions reduced *addiction scale* and *SMS addiction scale* by 0.08 to 0.16 standard deviations, or about 0.21–0.44 points on the 16-point *addiction scale*. Both interventions statistically significantly reduced the chance that people reported using their smartphones to relax to go to sleep, losing sleep from use, using longer than intended, using to distract from anxiety, having difficulty putting down their phone, using mindlessly, and other specific measures from the addiction scales; see online Appendix Figures A23 and A24. The limit treatment statistically significantly increased the extent to which people thought their smartphone use made their life better, while the bonus did not.

The bonus and limit treatments increased SWB by 0.09 standard deviations ( $p \approx 0.026$ ) and 0.04 standard deviations ( $p \approx 0.18$ ) respectively. The sharpened false discovery rate-adjusted *p*-values (see Benjamini and Hochberg 1995) are

<sup>16</sup>Online Appendix Figure A22 presents the treatment effects on survey outcomes separately for surveys 3 and 4. The limit effects on surveys 3 and 4 are statistically indistinguishable. Although the bonus did not substantially affect consumption in period 2, the bonus group reported more ideal use reduction and more addiction on survey 3. One potential explanation is that the bonus group hoped to reduce FITSBY use in anticipation of the period 3 incentive, and these survey responses reflect their failure to do so.

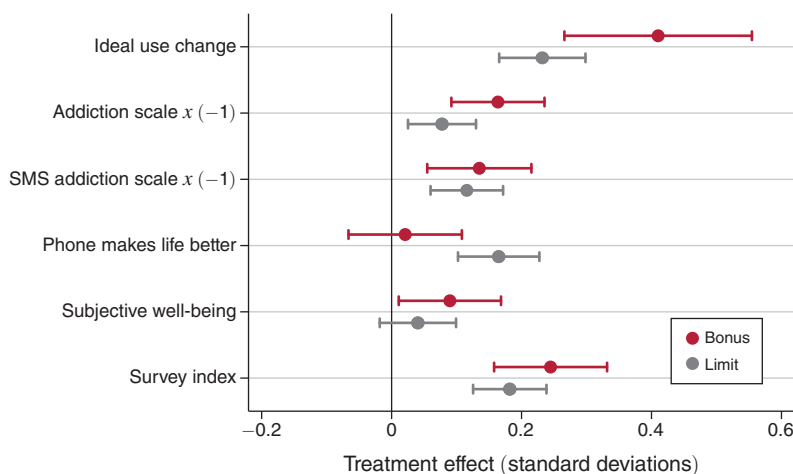


FIGURE 8. EFFECTS OF LIMITS AND BONUS ON SURVEY OUTCOME VARIABLES

*Notes:* This figure presents effects of the bonus and limit treatments on survey outcome variables using equation (4). The bonus effect is measured on survey 4, while the limit effect is measured on both surveys 3 and 4. *Ideal use change* is the answer to, “Relative to your actual use over the past 3 weeks, by how much would you ideally have [reduced/increased] your screen time?” *Addiction scale* is answers to a battery of 16 questions modified from the Mobile Phone Problem Use Scale and the Bergen Facebook Addiction Scale. *SMS addiction scale* is answers to shortened versions of the addiction scale questions delivered via text message. *Phone makes life better* is the answer to, “To what extent do you think your smartphone use made your life better or worse over the past 3 weeks?” *Subjective well-being* is answers to seven questions reflecting happiness, life satisfaction, anxiety, depression, concentration, distraction, and sleep quality; anxiety, depression, and distraction are reoriented so that more positive reflects better subjective well-being. *Survey index* combines the previous five variables, weighting by the inverse of their covariance at baseline.

0.09 and 0.24, respectively. These SWB effects appear to be driven particularly by improved concentration and reduced distraction; see online Appendix Figure A25. The effects of the bonus and limit on happiness, life satisfaction, depression, and anxiety are individually and collectively insignificant, while the effects of the bonus (but not the limit) on concentration, distraction, and sleep quality are collectively significant. Both interventions improved *survey index*, the inverse covariance-weighted average of the five survey outcome variables, by about 0.2 standard deviations.

One point of comparison for the SWB effects is Allcott et al. (2020). They find that deactivating subjects’ Facebook accounts for a four-week period increased an index of SWB by a statistically significant 0.09 standard deviations. Although the two interventions had similar effects on time use—deactivation in Allcott et al. (2020) reduced Facebook use by 60 minutes per day for 27 days, while our Screen Time Bonus reduced FITSBY use by 56 minutes per day for 20 days—they differed on a number of dimensions including the apps affected and the time period in which the study took place.

Online Appendix Figure A26 presents effects on *survey index* in subgroups with above- and below-median values of our six prespecified moderators. There is little heterogeneity with respect to the first four moderators, other than that the limit seems to have larger effects on women. However, the effects of both interventions are two to three times larger for people with above-median baseline values of *restriction index*, which measures interest in restricting smartphone time use, and *addiction index*. This implies that the interventions are well targeted: they have larger effects



for people who report wanting and needing them the most. Consistent with this, point estimates suggest that the bonus and limit both have larger effects on FITSBY use for people with higher *restriction index* and *addiction index*, although the differences are not as significant; see online Appendix Figure A27. This targeting result need not have been the case: for example, it could have been that more addicted people were less likely to feel that the limit functionality worked well for them.

## V. Estimating the Model

### A. Setup

We now turn to our model to simulate the effect of temptation on steady-state FITSBY use. In the model from Section I, temptation and habit formation interact, because the current consumption increase caused by temptation also increases future consumption. The long-run effect of temptation could therefore be different than any effects identified during the experiment. In this section, we estimate the model's structural parameters. In the next section, we simulate steady-state FITSBY use with counterfactual self-control and habit formation parameters.

We estimate the model using indirect inference: we derive equations that characterize how a consumer from our model would behave in our experiment, and we solve for the structural parameters consistent with the data. In our baseline estimates, we assume that all parameters other than  $\xi$  are homogeneous across consumers, although we relax this assumption in an extension that allows heterogeneity in temptation  $\gamma$  and perceived temptation  $\tilde{\gamma}$ .

In describing the estimation strategy, we focus on a “restricted model” where we set the anticipatory bonus effect  $\tau_2^B$  to zero. This implies full projection bias ( $\alpha = 1$ ), and thus that consumption decisions maximize current-period flow utility with no dynamic considerations. This substantially simplifies the exposition and, as we will show, has little impact on the results. Online Appendix E presents our “unrestricted model,” in which we use the empirical  $\tau_2^B$  and allow partial projection bias.

In the restricted model, consumers maximize current-period flow utility from equation (3), giving equilibrium consumption

$$(6) \quad x_t^*(s_t, \gamma, \mathbf{p}_t) = \frac{\zeta s_t + \xi_t - p_t + \gamma}{-\eta}.$$

We define  $\lambda := \frac{\partial x_t^*}{\partial s_t}$  as the effect of habit stock on consumption;  $\lambda = -\zeta/\eta$  in the restricted model. In a steady state with constant  $s$ ,  $\xi$ , and  $p$ , we must have  $s_{ss} = \rho(s_{ss} + x_{ss})$ , and thus  $s_{ss} = \frac{\rho}{1-\rho}x_{ss}$ .

We model the Screen Time Bonus as a price  $p^B = \$2.50$  per hour in period 3 plus a fixed payment.<sup>17</sup> We model the limit functionality as an intervention that eliminates share  $\omega$  of perceived and actual temptation. We conservatively assume

<sup>17</sup> Modeling the bonus as a linear price simplifies the model substantially, although it is an approximation: 13 percent of the bonus group hit the \$150 payment limit because they reduced period 3 FITSBY use by more than three hours per day relative to their bonus benchmark, and 3.5 percent used more than their bonus benchmark. These two subgroups in practice faced zero subsidy for marginal screen time reductions, although they may not have known that.

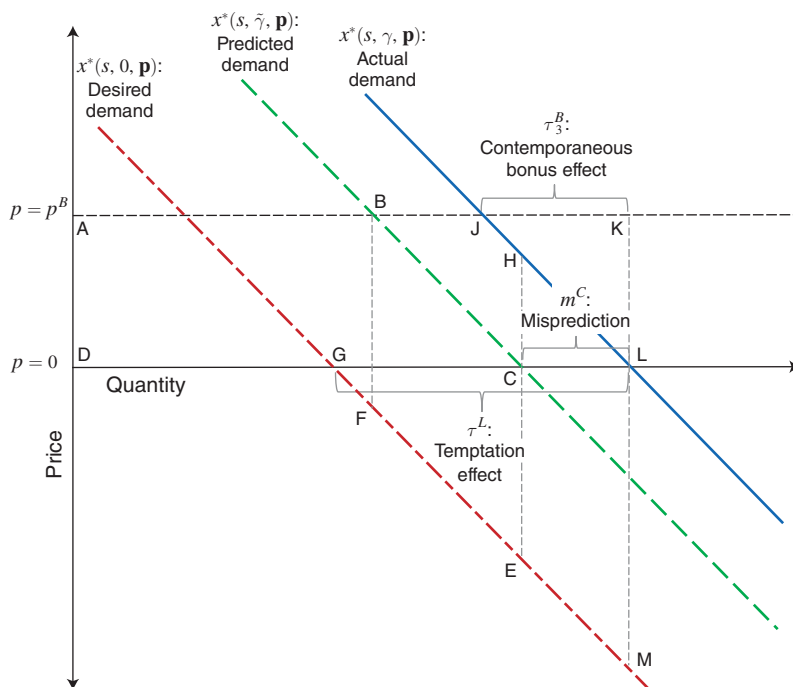


FIGURE 9. MODEL IDENTIFICATION

$\omega = 1$  in our primary estimates, and we consider alternative assumptions below. We assume that when predicting period  $t$  consumption on the survey at the beginning of period  $t$ , consumers use perceived temptation  $\tilde{\gamma}$  but are aware of projection bias, so the prediction is denoted  $x_t^*(s, \tilde{\gamma}, \mathbf{p}_t)$ .

Figure 9 illustrates temptation, naïveté, and our identification strategies. The three demand curves are desired demand  $x_t^*(s, 0, \mathbf{p}_t)$  according to preferences before period  $t$ , predicted demand  $x_t^*(s, \tilde{\gamma}, \mathbf{p}_t)$  as of survey  $t$ , and actual demand  $x_t^*(s, \gamma, \mathbf{p}_t)$ . The actual equilibrium at  $p = 0$  is point  $L$ , and the predicted equilibrium is at point  $C$ , so the distance  $CL$  is control group misprediction  $m^C := x_t^*(s, \gamma, \mathbf{p}_t) - x_t^*(s, \tilde{\gamma}, \mathbf{p}_t)$ . The bonus moves the equilibrium to point  $J$  in period 3, so the contemporaneous bonus effect  $\tau_3^B$  is the distance  $JK$ . The limit treatment moves the equilibrium to point  $G$ , so the limit treatment effect  $\tau^L$  is the distance  $GL$ .

### B. Estimating Equations

Unlike many applications of indirect inference, we derive equations that allow us to directly solve for the model parameters, so we do not need to use an optimization routine to search for parameters that fit the data. We estimate the parameters in stages, as parameters estimated in the first few equations are used as inputs to subsequent equations. We estimate confidence intervals by bootstrapping. Online Appendix G presents formal derivations and additional details.

*Habit Formation.*—We first estimate  $\rho$  from the decay of the bonus treatment effects. Taking the expectations over  $\xi$  in the bonus and bonus control groups, we can write the average treatment effect of the bonus on period 4 consumption as the result of the decayed period 3 effect. Similarly, the average treatment effect in period 5 results from the cumulative decayed effects from periods 3 and 4:

$$(7) \quad \tau_4^B = \lambda \rho \tau_3^B,$$

$$(8) \quad \tau_5^B = \lambda(\rho \tau_4^B + \rho^2 \tau_3^B).$$

Dividing those two equations gives

$$(9) \quad \rho = \frac{\tau_5^B}{\tau_4^B} - \frac{\tau_4^B}{\tau_3^B}.$$

This equation shows that if the bonus effect is more persistent between periods 4 and 5, we infer that habit stock is more persistent (a larger  $\rho$ ).

In the unrestricted model in online Appendix E, we also estimate  $\lambda$ , because it is useful in estimating the other parameters. To provide a comparison, we also estimate  $\lambda$  in the restricted model by rearranging equation (7) and inserting the  $\rho$  from equation (9):  $\lambda = \frac{\tau_4^B}{\rho \tau_3^B}$ .

*Price Response and Habit Stock Effect on Marginal Utility.*—After estimating  $\rho$ , we estimate  $\eta$  and  $\zeta$  from the magnitude and decay of the bonus treatment effects. For each of periods 3 and 4, we take the expectations over  $\xi$  of equilibrium consumption in the bonus and bonus control groups, difference the two, and rearrange, giving

$$(10) \quad \eta = \frac{p^B}{\tau_3^B},$$

$$(11) \quad \zeta = \frac{-\eta \tau_4^B}{\rho \tau_3^B}.$$

Figure 9 illustrates the first equation: the inverse demand slope  $\eta$  is just the ratio of  $p^B$  (the vertical distance  $KL$ ) to  $\tau_3^B$  (the horizontal distance  $JK$ ). The second equation shows that if the bonus effect is more persistent between periods 3 and 4, we infer that habit stock has a larger effect on marginal utility (a higher  $\zeta$ ).

*Naïveté about Temptation.*—Next, we estimate naïveté about temptation  $\gamma - \tilde{\gamma}$  using misprediction in the control group. To solve for  $\gamma - \tilde{\gamma}$ , we take the expectations over  $\xi$  of actual consumption and consumption as predicted at the beginning of the period, difference the two, and rearrange, giving

$$(12) \quad \gamma - \tilde{\gamma} = -\eta m^C.$$

Figure 9 illustrates: naïveté  $\gamma - \tilde{\gamma}$  is the vertical distance  $HC$  between actual and predicted marginal utility, and this can be inferred by multiplying control group average misprediction  $m^C$  (the horizontal distance  $CL$  between actual and predicted demand) by the inverse demand slope  $\eta$ .

*Temptation.*—To estimate temptation  $\gamma$ , we take the expectations over  $\xi$  of equilibrium consumption in the limit and limit control groups, difference the two, and rearrange, giving

$$(13) \quad \gamma = \eta \tau_2^L.$$

Figure 9 illustrates: temptation  $\gamma$  is the vertical distance  $LM$  between desired and actual demand, and this can be inferred by multiplying the effect of removing temptation ( $\tau_2^L$ , the horizontal distance  $GL$  between long-run and present demand) by the inverse demand slope  $\eta$ . We then substitute the estimated  $\gamma$  into equation (12) to infer  $\tilde{\gamma}$ .

*Intercept.*—Finally, we back out the distribution of  $\xi$  that fits the distribution of baseline consumption. We assume that participant  $i$ 's baseline consumption  $x_{i1}$  was in a steady state. Substituting  $s_{ss} = \frac{\rho}{1-\rho} x_{ss}$  into equilibrium consumption from equation (6) and rearranging gives

$$(14) \quad \xi_i = p - \gamma + x_{i1} \left( -\eta - \zeta \frac{\rho}{1-\rho} \right).$$

This equation shows that we infer larger  $\xi_i$  for people with higher baseline consumption  $x_{i1}$ .

In the unrestricted model in online Appendix E, equilibrium consumption also depends on  $\phi$ , the direct effect of habit stock on utility. Our data do not allow us to separately identify  $\phi$  from  $\xi$ , so we estimate an “intercept”  $\kappa_i := (1 - \alpha)\delta\rho(\phi - \xi_i) + \xi_i$  that includes both of these structural parameters. In the restricted model with  $\alpha = 1$ , this simplifies to  $\kappa_i = \xi_i$ .

### C. Empirical Moments

Table 3 presents the moments used to estimate the restricted model. The bonus and limit effects  $\tau_t^B$  and  $\tau_2^L$  are as displayed in Figure 4. Control group misprediction  $m^C$  is the average across periods 2–4 of the difference between actual period  $t$  FITSBY use and the prediction for period  $t$  elicited on survey  $t$ , as displayed in Figure 6. The unrestricted model and our robustness checks also use the anticipatory bonus effect  $\tau_2^B$  and additional parameters presented in online Appendix Table A7. In light of the discussion in Section IVC, we omit the first half of period 2 when we estimate  $\tau_2^B$ .<sup>18</sup>

<sup>18</sup>Online Appendix Table A8 presents parameter estimates when we use all of period 2 to estimate  $\tau_2^B$ . The estimated projection bias  $\alpha$  is smaller, as expected, but the other parameter estimates are very similar.

TABLE 3—EMPIRICAL MOMENTS FOR RESTRICTED MODEL ESTIMATION

Parameter	Description	Point estimate (1)	Confidence interval (2)
$\tau_3^B$	Contemporaneous bonus effect (minutes/day)	−55.9	[−61.7, −50.3]
$\tau_4^B$	Long-term bonus effect (minutes/day)	−19.2	[−24.7, −13.7]
$\tau_5^B$	Long-term bonus effect (minutes/day)	−12.3	[−18.1, −6.54]
$\tau_2^L$	Limit effect (minutes/day)	−24.3	[−28.1, −20.4]
$m^C$	Control group misprediction (minutes/day)	6.13	[4.52, 7.72]
$\bar{x}_1$	Average baseline use (minutes/day)	153	[149, 157]

*Note:* This table presents point estimates and bootstrapped 95 percent confidence intervals for the empirical moments used for our primary estimates of the restricted model.

TABLE 4—PRIMARY PARAMETER ESTIMATES

Parameter	Description (units)	Restricted model ( $\tau_2^B = 0, \alpha = 1$ ) (1)	Unrestricted model ( $\alpha = \hat{\alpha}$ ) (2)
$\lambda$	Habit stock effect on consumption (unitless)	1.15 [0.609, 3.31]	1.12 [0.572, 3.16]
$\rho$	Habit formation (unitless)	0.299 [0.106, 0.493]	0.302 [0.106, 0.498]
$\alpha$	Projection bias (unitless)	1	0.897 [0.584, 1.00]
$\eta$	Price coefficient (\$-day/hour <sup>2</sup> )	−2.68 [−2.98, −2.43]	−2.75 [−3.04, −2.51]
$\zeta$	Habit stock effect on marginal utility (\$-day/hour <sup>2</sup> )	3.08 [1.65, 8.97]	3.01 [1.55, 8.57]
$\gamma - \tilde{\gamma}$	Naïveté about temptation (\$/hour)	0.274 [0.201, 0.349]	0.278 [0.205, 0.354]
$\gamma$	Temptation (\$/hour)	1.09 [0.884, 1.30]	1.11 [0.903, 1.33]
$\bar{\kappa}$	Average intercept (\$/hour)	−2.41 [−3.62, −1.10]	−2.24 [−3.53, −0.803]

*Note:* This table presents point estimates and bootstrapped 95 percent confidence intervals from the estimation strategy described in Section VB and online Appendix E.3.

#### D. Parameter Estimates

Table 4 presents our point estimates and bootstrapped 95 percent confidence intervals. Column 1 presents the restricted model described above (fixing  $\tau_2^B = 0$  and  $\alpha = 1$ ), while column 2 presents the unrestricted model described in online Appendix E. Since the estimated  $\tau_2^B$  is close to zero and  $\hat{\alpha}$  is close to one, the estimates in the two columns are very similar.

In column 1, we estimate  $\hat{\lambda} \approx 1.15$  and  $\hat{\rho} \approx 0.299$ . In our model, this implies that an exogenous consumption increase of 1 minute per day over a 3-week period will cause consumption to increase by  $\hat{\lambda}\hat{\rho} \approx 0.34$  minutes per day in the next 3-week period, and  $\hat{\lambda}\hat{\rho}^2 \approx 0.10$  minutes per day in the period after that.

Consistent with the small and statistically insignificant anticipatory bonus effect  $\tau_2^B$  in the second half of period 2, we estimate  $\hat{\alpha} \approx 0.897$  in the unrestricted model in column 2, which is marginally significantly different from 1. The point estimate suggests that participants were attentive to only  $(1 - \hat{\alpha}) \times 100$  percent  $\approx 10.3$  percent of habit formation. Inserting the estimates of  $\lambda$ ,  $\rho$ ,  $\eta$ , and  $\zeta$  into equation (24) in online Appendix E, we calculate that  $\tau_2^B$  would have needed to be  $-16.1$  minutes per day (compared to the actual point estimate of  $-1.96$  minutes per day in the second half of period 2) to estimate zero projection bias ( $\alpha = 0$ ). In other words, the anticipatory bonus effect is only 12 percent of what our model would predict with fully forward-looking (“rational”) habit formation. This is striking when combined with the evidence from Figure 7 that participants correctly predicted habit formation. It is consistent with a model in which people are intellectually aware of habit formation but consume as if they are inattentive to it.

Since the restricted model estimating equations are so simple, one can easily calculate the point estimates in column 1 with the moments from Table 3. For example, the control group underestimated FITSBY use by an average of 6.13 minutes per day on surveys 2–4. Inserting that into equation (12) gives a naïveté of  $\widehat{\gamma - \tilde{\gamma}} = -\hat{\eta} \cdot m^C \approx -(-2.68) \cdot (6.13/60) \approx \$0.274$  per hour in column 1.

The limit changed period 2 FITSBY use by  $-24.3$  minutes per day. Inserting that into equation (13) gives temptation  $\hat{\gamma} = \hat{\eta} \tau_2^L \approx (-2.68) \cdot (-24.3/60) \approx \$1.09$  per hour in column 1. This estimate implies that a tax on FITSBY use of \$1.09 per hour would reduce consumption to the level our participants would choose for themselves in advance. Dividing estimated naïveté  $\widehat{\gamma - \tilde{\gamma}}$  by this  $\hat{\gamma}$  suggests that our participants underestimate temptation by  $0.274/1.09 \times 100$  percent  $\approx 25$  percent.

Online Appendix E.5 presents alternative estimates of temptation  $\gamma$  in the restricted and unrestricted models. First, we infer perceived temptation using participants’ valuations of the limit functionality and the Screen Time Bonus, following Acland and Levy (2012); Augenblick and Rabin (2019); Chaloupka, Levy, and White (2019); Allcott et al. (2022); and Carrera et al. (2021). Second, we generalize the model to include multiple temptation goods, using the self-reports of substitution to FITSBY use on other devices discussed in Section IVE. Third, we assume that the limit treatment eliminates share  $\omega \in [0, 1]$  of temptation, relaxing the assumption of  $\omega = 1$  in our primary estimates; we estimate  $\omega$  from differences in self-reported *ideal use change* between the limit and limit control groups. Finally, we allow for individual-specific heterogeneity in  $\gamma$ , using the distribution of *limit tightness* set by limit group participants. These alternative approaches all imply temptation  $\gamma$  between about \$1 and \$3 per hour, and our primary estimate of \$1.09 per hour is relatively conservative.

## VI. Counterfactuals: Effects of Temptation on Time Use

### A. Methodology

Using the parameter estimates from the previous section, we can predict the effects of changes in temptation and habit formation on steady-state FITSBY use. Equation (21) in online Appendix E characterizes steady-state consumption in the unrestricted model. Using that equation, we can predict participant  $i$ ’s steady-state



FITSBY use at  $p = 0$  as a function of any values of habit formation, temptation, and steady-state misprediction parameters  $\{\zeta, \gamma, \tilde{\gamma}, m_{ss}\}$ :

$$(15) \quad \hat{x}_{i,ss}(\zeta, \gamma, \tilde{\gamma}, m_{ss}) = \frac{\hat{\kappa}_i + (1 - \hat{\alpha})\delta\hat{\rho}\left[(\zeta - \hat{\eta})m_{ss} - \left(1 + \hat{\lambda}\right)\tilde{\gamma}\right] + \gamma}{-\hat{\eta} - (1 - \hat{\alpha})\delta\hat{\rho}(\zeta - \hat{\eta}) - \zeta\frac{\hat{\rho} - (1 - \hat{\alpha})\delta\hat{\rho}^2}{1 - \hat{\rho}}}.$$

The sample average prediction is denoted  $\bar{\hat{x}}_{ss}(\zeta, \gamma, \tilde{\gamma}, m_{ss})$ . As discussed in online Appendix E.3, we assume that the predicted  $\hat{\lambda}$  equals the estimated  $\hat{\lambda}$ , that steady-state misprediction  $m_{ss}$  equals observed control group misprediction  $m^C$ , and that the discount factor is  $\delta = 0.997$  per 3-week period, consistent with a 5 percent annual discount rate.

Since we can't identify  $\phi$  (the direct effect of habit stock on utility), we must hold constant each participant's intercept  $\kappa_i := (1 - \alpha)\delta\rho(\phi - \xi_i) + \xi_i$  across counterfactuals in the restricted model. Since this intercept contains  $\rho$  and  $\alpha$ , we can't predict consumption with counterfactual values of  $\rho$  or  $\alpha$ .

In the restricted model with  $\alpha = 1$ , equation (15) simplifies to

$$(16) \quad \hat{x}_{i,ss}(\rho, \gamma) = \frac{\hat{\xi}_i + \gamma}{-\hat{\eta} - \hat{\zeta}\frac{\rho}{1 - \rho}},$$

which could also be derived from substituting  $s_{ss} = \frac{\rho}{1 - \rho}x_{ss}$  into equation (6). Steady-state misprediction  $m_{ss}$  and perceived temptation  $\tilde{\gamma}$  do not affect steady-state consumption in the restricted model because consumers simply maximize current-period flow utility.

## B. Counterfactual Results

Figure 10 presents point estimates and bootstrapped 95 percent confidence intervals for predicted average FITSBY use at counterfactual parameter values. For each counterfactual, we present predictions from the restricted model ( $\alpha = 1$ ) and unrestricted model ( $\alpha = \hat{\alpha}$ ). We label the restricted model predictions as our primary results, because they are simpler and more conservative.

The first "counterfactual" is the baseline at our point estimates:  $\hat{x}_{ss}(\hat{\zeta}, \hat{\gamma}, \hat{\gamma}, \hat{m}^C)$ . This mechanically matches baseline average FITSBY use of 153 minutes per day. The second counterfactual removes naïveté:  $\bar{\hat{x}}_{ss}(\hat{\zeta}, \hat{\gamma}, \hat{\gamma}, 0)$ .<sup>19</sup> As described above, naïveté has no effect when  $\alpha = 1$ . Because naïveté is so small and projection bias is so strong, the point estimate with  $\alpha = \hat{\alpha}$  is very close to the baseline.

The third counterfactual removes temptation:  $\bar{\hat{x}}_{ss}(\hat{\zeta}, 0, 0, 0)$ . Relative to baseline, removing temptation reduces predicted FITSBY use by 48 minutes per day (31 percent) with  $\alpha = 1$ . Thus, our primary estimate is that smartphone FITSBY use would be 31 percent lower without self-control problems.

The fourth and fifth counterfactuals remove habit formation, first with temptation and then without:  $\bar{\hat{x}}_{ss}(0, \hat{\gamma}, \hat{\gamma}, \hat{m}^C)$  and then  $\bar{\hat{x}}_{ss}(0, 0, 0, 0)$ . We emphasize that

<sup>19</sup>Since Figure 7 shows that participants predicted habit formation fairly accurately, we attribute all of steady-state misprediction  $m_{ss}$  to naïveté about temptation.

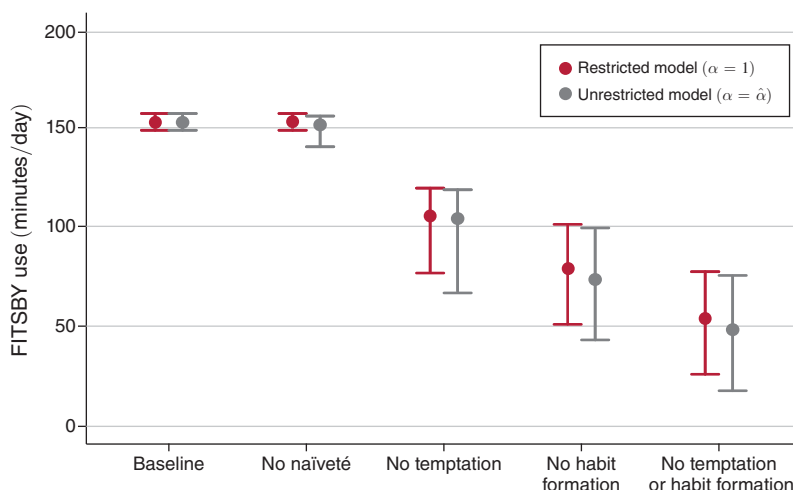


FIGURE 10. EFFECTS OF TEMPTATION AND HABIT FORMATION ON FITSBY USE

Note: This figure presents point estimates and bootstrapped 95 percent confidence intervals for predicted steady-state FITSBY use with different parameter assumptions, using equation (15).

habit formation on its own is not a departure from rationality (Becker and Murphy 1988), and it could capture forces such as learning and investment that increase consumer welfare. Relative to baseline, removing habit formation reduces predicted FITSBY use by 75 minutes per day with  $\alpha = 1$ . Without habit formation, the effect of removing temptation (going from the fourth to the fifth counterfactual) is just the limit treatment effect ( $\tau_2^L \approx -24.3$  minutes per day), which is about one-half of the effect of removing temptation with habit formation (47.5 minutes per day with  $\alpha = 1$ ).<sup>20</sup> This quantifies how habit formation magnifies the effects of temptation, because current temptation increases current consumption and thus future demand.

We highlight one important tension in our results: Figure 4 shows that the limit effects decay slightly over periods 2–5, while our model predicts that the limit effects should grow over time as the limit group's habit stock diminishes. One potential explanation is that habit formation works differently in response to prices versus self-control tools. Another potential explanation is that motivation to use the limit functionality decays enough that it outweighs the habit stock effect.

Online Appendix Table A15 presents 19 alternative estimates of the effects of temptation on steady-state FITSBY use across the restricted and unrestricted models. Consistent with the fact that our primary estimates of  $\gamma$  are smaller than most alternative estimates, our primary estimates of the steady-state temptation effects are also relatively conservative. Furthermore, weighting our sample on observables to look more like the US adult population also increases the predicted effects of temptation on consumption. This means that while our sample may still be nonrepresentative on

<sup>20</sup> Without habit formation, the effect of removing temptation on  $\bar{x}_{ss}$  is  $\hat{\gamma}/-\hat{\eta}$ , which equals  $\tau_2^L$  after substituting  $\hat{\gamma} = \tau_2^L \hat{\eta}$ .

unobservable characteristics, sample selection bias captured by observables causes us to *understate* the effects of temptation on FITSBY use.<sup>21</sup>

Since we don't identify  $\phi$  (the direct effect of habit stock on utility), we can't do a full welfare analysis. The relatively elastic demand—from Section IVC, 39 percent of consumption is worth less than \$2.50 per hour—suggests that participants do not have strong preferences over how to spend this marginal time, so the welfare losses from self-control problems might be limited. On the other hand, even small individual-level losses might be substantial when aggregated over many social media users. In a static model, the deadweight loss from temptation would be the triangle *GLM* on Figure 9:  $-\tau^L\gamma/2 \approx -(-24.3/60) \times 1.09/2 \approx \$0.22$  per day, or \$4.62 per three-week period. This is closely consistent with the average valuation of \$4.20 for three weeks of access to the limit functionality. Aggregated across 240 million American social media users (Pew Research Center 2021), this would be  $\$4.62 \times (52/3) \times 0.24 \approx \$19.2$  billion per year in welfare losses from overuse of social media caused by self-control problems. For comparison, Facebook's total global profits in 2020 were \$29 billion (US Securities and Exchange Commission 2020). However, we don't know how these effects would cumulate over time, as represented by  $\phi$ : for example, after a longer period of reduced screen time, people might find more peace of mind or regret the loss of online interactions with friends and family.

## VII. Conclusion

While digital technologies provide important benefits, some argue that they can be addictive and harmful. We formalize this argument in an economic model and transparently estimate the parameters using data from a field experiment. The Screen Time Bonus intervention had persistent effects after the incentives ended, suggesting that smartphone social media use is habit forming. Participants predicted these persistent effects on surveys but did not reduce FITSBY use before the bonus was in effect, suggesting that they are aware of but inattentive to habit formation. Participants used the screen time limit functionality when we offered it in the experiment, and this functionality reduced FITSBY use by over 20 minutes per day, suggesting that social media use involves self-control problems. The control group repeatedly underestimated future use, suggesting slight naïveté. Many participants reported indicators of smartphone addiction on surveys, and both the bonus and limit interventions reduced this self-reported addiction. Looking at these facts through the lens of our economic model implies that self-control problems magnified by habit formation might be responsible for 31 percent of social media use. These results suggest that better aligning digital technologies with well-being should be an important goal of users, parents, technology workers, investors, and regulators.

<sup>21</sup>Online Appendix Tables A11–A13 present the demographics, moments, and parameter estimates in the weighted sample. Online Appendix Table A14 presents the numbers plotted in Figure 10. Online Appendix Figure A35 presents the distribution of modeled temptation effects across participants, using the limit group's distribution of *limit tightness* to identify heterogeneity in temptation. The effect is less than 10 minutes per day for 26 percent of participants, and over 100 minutes per day for 13 percent.

Our results raise many additional questions; here are two. First, what are the underlying mechanisms and microfoundations that generate the persistent bonus treatment effects? We model this persistence simply through a capital stock of past consumption, but it could be driven by learning (followed by forgetting), network investments (e.g., connections with friends ebb and flow if maintained or neglected), or more nuanced habit formation mechanisms involving cues or automaticity (e.g., Laibson 2001; Bernheim and Rangel 2004; Wellsjo 2021). Second, if so many of our participants perceive self-control problems and use (and are willing to pay for) the Phone Dashboard time limit functionality, why isn't there higher demand for commercial digital self-control tools? Only 5 percent of our sample reported using any apps to limit their smartphone use at baseline. Potential explanations include that our experimental setting or selected set of participants overstates demand for commitment, that commercial self-control tools are too expensive or are ineffective because it's too easy to evade them or substitute across devices, that people aren't aware of existing tools, that the time misallocated due to temptation is not very valuable, or that the commitment and flexibility features we built into Phone Dashboard were better suited to people's needs. We leave these questions for future work.

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