Temporal Reframing and Participation in a Savings Program: A Field Experiment

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Abstract. A growing percentage of American workers are now freelancers and thus responsible for their own retirement savings, yet they face a number of psychological hurdles that hamper them from saving enough money for the long-term. Although prior theory-derived interventions have been successful in addressing some of these obstacles, encouraging participation in saving programs is a challenging endeavor for policymakers and consumers alike. In a field setting, we test whether framing savings in more or less granular formats (e.g., saving daily versus monthly) can encourage continued saving behavior through increasing the take-up of a recurring deposit program. Among thousands of new users of a financial technology app, we find that framing deposits in daily amounts as opposed to monthly amounts quadruples the number of consumers who enroll. Further, framing deposits in more granular terms reduced the participation gap between lower and higher income consumers: three times as many consumers in the highest rather than lowest income bracket participated in the program when it was framed as a \$150 monthly deposit, but this difference in participation was eliminated when deposits were framed as \$5 per day.

Keywords: choice architecture, behavioral economics, saving, field experiment, financial technology

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1. Introduction

People often have difficulty saving money and marketers face problems convincing them to do so, a challenge that exists regardless of whether goals and time horizons are short- or longterm. For example, consumers have trouble saving for long-term goals like retirement (e.g., Benartzi and Thaler 2013) and college education (Madrian et al. 2017). But, people are also challenged by the prospect of saving for emergencies that may arise in the short-term: in a recent government report, nearly half of adults said they either could not handle an emergency expense of a few hundred dollars or would have to cover the emergency through selling something or borrowing money (Board of Governors of the Federal Reserve System 2016; see also Lusardi, Schneider, and Tufano 2011).

Prior behavioral economic interventions have been successful in addressing psychological obstacles that hamper people from choosing to save. Automatically enrolling eligible employees into employer-sponsored saving plans (i.e., defined contribution plans) results in a dramatically greater percentage of employees actively saving (Madrian and Shea 2001), although some plans still set default savings rates too low relative to what would be more effective (Beshears et al. 2009). The Save More Tomorrow program, for example, directly addresses psychological obstacles to saving, such as myopia, inertia, and loss aversion (Thaler and Benartzi 2004), by introducing pre-commitment and automatic savings rate escalators that are synchronized with future salary increases. Such programs have helped millions of Americans be more actively prepared for retirement (Benartzi and Thaler 2013). In similar fashion, global policy efforts have been introduced to help increase participation in saving programs. In the United Kingdom, for example, the Pensions Act 2008 mandates that employers auto-enroll certain employees into retirement savings plans (Parliament of the United Kingdom, 2016).

Similarly, in the United States, rulemaking at the federal level has outlined guidance and provided safe harbors that have ultimately facilitated state-level efforts to both overcome roadblocks and start to permit the benefits of auto-enrollment to be expanded to non-employer savings arrangements, namely IRAs (US Department of Labor, Employee Benefits Security Administration, 2016). Despite the success of these and similar programs, consumers and policymakers still face major hurdles when it comes to encouraging participation in saving programs.

One of these hurdles, as typified in saving for retirement, is that existing solutions have largely focused on employees with access to a retirement savings plan (e.g., 401k plan). Furthermore, the solutions were designed for an era where employees were predominantly employed full-time and tended to receive paychecks on a regular but relatively infrequent basis, such as bi-weekly or monthly. These traditional employment arrangements are increasingly obsolete, as more workers are part of the so-called gig economy, which consists of more selfemployed, part-time, and on-demand workers. Indeed, the U.S. Government Accountability Office estimated that "contingent workers" (i.e., on-call, part-time, and self-employed workers) make up more than a third of the total employment workforce (GAO 2013), and companies considered part of the on-demand economy (e.g., Uber, Lyft, Amazon Mechanical Turk) comprise around 21 million workers internationally (de Stefano 2015). One assessment even suggests that alternative employment arrangements accounted for nearly 85 percent of employment growth between 2005 and 2013 (Friedman 2014). This distinction between traditional employment arrangements and alternative arrangements is important as gig economy workers may be paid on more granular time intervals than traditional workers. For example, Uber drivers work when they want and get paid weekly (Cramer and Krueger 2016), and Amazon Mechanical Turk workers may complete tasks and have them approved by different task requesters in minutes, and request payment distributions and have them paid daily (Paolacci and Chandler 2014).

Given this shift toward more granular payment structures, we test whether framing savings in more or less granular formats (e.g., saving daily versus monthly) can encourage continued saving behavior through increasing the take-up of a recurring deposit program. Because people may create separate mental accounts for small compared to large losses of money (e.g., Thaler 1985), our specific research objective is to test whether people are less sensitive to present-day losses (which will turn into future gains) when such losses are framed in a smaller, more granular format (e.g., \$5 a day) compared to a larger, less granular format (e.g., \$150 a month). We draw on three related literatures to generate this hypothesis.

First, financially equivalent sums of money can be presented in formats with different psychological associations. For example, when workers near retirement, they have the option to cash out their savings in a lump sum (e.g., \$100,000) or purchase an annuity and receive an equivalent amount, spread out monthly for life (e.g., \$500 per month from age 68 onward). Yet, consumers are more sensitive to changes in wealth when income is expressed in a monthly framing compared to a lump sum framing (Goldstein, Hershfield, and Benartzi 2016; Goda, Manchester, and Sojourner 2013). This leads to an "illusion of wealth," whereby lump sums seem more adequate than an equivalent monthly income at lower wealth levels (when consumers can adequately perceive just how *little* a monthly amount would afford), with a reversal of this pattern at higher levels of wealth (when consumers can adequately perceive just how much a monthly amount would afford). That is, at lower wealth levels, a lump sum may seem subjectively larger than its equivalent monthly amount, thus affording a perception of greater adequacy.

In the current investigation, we examine whether this same psychological phenomenon can be used to help people regularly contribute to a savings account in a field setting with consequential outcomes. If consumers perceive that lump sums afford greater spending power than equivalent amounts framed in more granular ways, then it stands to reason that parting with such lump sums should be more psychologically painful than giving up an equivalent amount of money spread out over time in a smaller, more granular format (i.e., a "pennies-a-day" framing; Gourville 1998). Concretely, when consumers enroll in some saving plans, they are given the opportunity to set up a recurring deposit and regularly contribute a given amount of money to their account. These contributions are often framed in terms of a monthly contribution (e.g., \$150 a month), likely reflecting traditional paycheck and banking norms where money is only transferred from one account to another on a monthly basis. But these same monthly contributions could be instead represented by weekly (e.g., \$35 a week) or even daily (e.g., \$5 a day) amounts. Goldstein et al. (2016) found that a lump sum of \$100,000 felt subjectively larger than its equivalent annuity of \$500 per month. Likewise, larger monthly amounts of money (e.g., \$150) may be more psychologically painful to give up than equivalent, smaller weekly (e.g., \$35) or daily (\$5) amounts of money. As a result, we predict that consumers will be more likely to enroll in a recurring deposit program when deposits are framed in a more granular way (i.e., when parting with the recurring deposit seems less psychologically painful) than when deposits are framed in a less granular way.

Second, in research from the "pennies-a-day" literature, temporally reframing the cost of a product into more granular amounts increased purchase intent in laboratory settings, in part because doing so reduced the perceived cost of the deal (Gourville 1998, 1999; Nagle and Holden 1995). This general preference for less aggregate framing over more aggregate framing

extended from days to larger units such as weeks and months (paying \$1 per day is preferred to paying \$365 per year), but this finding reverses with larger monetary amounts (paying \$4,200 per year is preferred to paying \$11.50 per day; Gourville 2003). Although much of the literature on temporal reframing has focused on cost perceptions in purchasing domains, we view these as relevant to saving decisions as well: when deciding whether to save or spend money now, one factor that consumers must consider is how painful it will be to give up (i.e., "pay") a certain amount of money now for larger gains later. Indeed, people at least seem to think that such framing can be helpful in the savings domain: Colby and Chapman (2013), for example, found that consumers thought they would be more likely to forgo small expenditures in order to put money toward a savings goal, but only when such goals were framed in a more granular format. Notably, the literature to date has not investigated the effectiveness of such temporal framing in a field setting with consequential financial outcomes.

Third, a growing body of research has suggested that one barrier to future-oriented behavior is the tension that consumers feel between what they may want to do in the present versus what they think they should do for the future (Bazerman, Tenbrunsel, and Wade-Benzoni 1998). In an effort to help consumers with such intertemporal dilemmas, researchers have attempted to enhance the sense of emotional connection that is felt between current and future selves: when the future self is made to feel emotionally closer to the current self, consumers are more likely to delay financial rewards (Bartels and Urminsky 2011) and increase their retirement contributions (Bryan and Hershfield 2012). However, increasing this sense of connection between selves can be costly and difficult to execute. As a result, another type of intervention may be effective: rather than trying to directly influence the relationship between current and future selves, it may be useful to frame the sacrifices made by the current self as less onerous in

nature (Hershfield 2018). Along these lines, framing savings contributions in less "painful" ways (i.e., in more temporally granular ways) may increase the likelihood that a consumer would be willing to make a present-day sacrifice for future gains.

Given the importance of investigating whether these effects extend to real-world settings. and the growing interest from policy-makers in encouraging participation in saving programs, we set out to conduct a field study with a financial technology company (Acorns) that provides a mobile phone app allowing people to save and invest in small (e.g., spare change) and large amounts (e.g., thousands of dollars). In the course of our research, new users were given the opportunity to set up a recurring deposit program, in an effort to get them to save regularly. Critically, when users were invited to join the recurring deposit program, they were offered deposits in terms of either daily, weekly, or monthly amounts. Drawing on the various literature streams reviewed above, we hypothesized that users would be more likely to enroll in the recurring deposits program when deposits were framed as more granular, and less psychologically painful. That is, the probability of enrolling will be greater for daily over weekly over monthly framing of the same total amounts.

2. Method

Participants in the field study were new users to the Acorns app. We aimed to have approximately 2,000 users in each of five conditions or run the sign-up period of the field study for approximately 4 weeks, whichever came first. The sign-up period ran from January 4th to January 31st, 2017, and we concluded with 8,931 total participants.

2.1 Sample Characteristics

The average age of participants was 32.81 years (SD = 10.19 years). In terms of household income, 25.4% had less \$25,000 a year, 37.8% had between \$25,000 and \$49,999, 29.5% had between \$50,000 and \$99,999, 6.9% had between \$100,000 and \$249,999, and .6% had above \$250,000. Users were not required to report their sex, and only 1.737 or 19% of the sample did; of those, 551 were women and 1,186 were men.

To sign up for an Acorns account, a user has to download the Acorns app to his or her smartphone. From there, they must provide an email address for logging in, affirm they are a U.S. resident who is 18 years of age or older, agree to an Acorns program agreement, connect a bank account using their bank credentials, and provide some personal information (e.g., name, home address, phone number, and social security identification) to open an investment account. Users are also asked to furnish information about their income, net worth, and investment goals to help Acorns recommend a pre-designed investment portfolio, which reflects a mix of exchange traded funds (often representing an asset class or index like the S&P 500) in one of five configurations: conservative, moderately conservative, moderately aggressive, or aggressive. Fees for an Acorns account are \$1 per month for an account less than \$5,000 and 0.25% per year for an account greater than or equal to \$5,000.

2.2 Procedure

After signing up for an account with Acorns, users were asked if they wanted to make an initial one-time deposit to their accounts, and were presented with five options for that initial deposit (one of which was a free-response and the other four options were based on the user's income level; See Table S1 in the Appendix for full set of options). If a given user decided to make an initial deposit¹, they were then randomly assigned to receive one of five different

¹ Approximately 45% of users opted to make an initial deposit. Although it would have been desirable to compare those who made an initial deposit versus those who did not, we were not given access to data from the users who did not make an initial deposit. Furthermore, it may have been desirable to have an experimental design in which all new users were given access to the recurring deposit program, and not just the users who elected to make an initial deposit. For business reasons, however, it did not make sense to ask users who had declined an initial deposit to then sign up for a recurring deposit program, as doing so may have caused them to exit from the sign-up process.

treatments, which asked whether they would like to set up a recurring deposit that varied the dollar amount and temporal frame. (We discuss implications of this design in the Discussion section). This message represents the central component of the field study that we conducted. Because randomization was conducted using a truly random allocation procedure, the number of users who were assigned to each condition was not equal across conditions. In three of the conditions, users would deposit a total of approximately \$150 a month, but deposits were framed in daily, weekly, or monthly amounts: 1) \$5 a day (1,772 users), 2) \$35 a week (1,826 users), or 3) \$150 a month (1,744 users), and in two additional conditions, users would deposit a total of approximately \$30 a month, framed in weekly or monthly amounts: 4) \$7 a week (1,817 users) and 5) \$30 a month (1,772 users). To check the validity of the random assignment, we compared the distribution of those variables that were reported by all participants and found that random assignment was in fact valid, as there were no differences across condition in terms of age (F(4, 8926) = .62, p = .65), initial deposit $(F(4, 8910^3) = .93, p = .44)$, or the categorical income variable (χ^2 (4, N = 8931) = 15.26, p = .51). See Table 1 for descriptive statistics by condition.

Users could elect to either enroll in the recurring deposit program or do so at a later time. Note that when users elect to participate in the recurring deposit program, money is pulled either on a daily, weekly, or monthly basis based on their assigned condition, provided that any weekend day pulls are postponed until the following Monday.

Once users had made their decision regarding recurring deposits, they were free to use the app as they wished. See Figure 1 for a flowchart of the sign-up process, including the critical recurring deposit intervention. After this initial sign-up, we continued to monitor users for 3

² Note that we were unable to implement \$1 per day due to technical limitations identified by Acorns.

³ Initial deposit data was missing for 16 participants.

months at approximately 5-week, 7-week, 8-week, 10-week, and 12-week intervals, during which we were able to assess whether users had left the recurring deposit feature on or turned it off (allowing us to assess retention as a function of condition). During this period of time, we also monitored total account balance⁴.

3. Results

Our interest in conducting this field study concerned whether framing monetary contributions in a more granular manner would increase participation in a recurring deposit program. Thus, we treated the first three conditions (\$5 a day, \$35 a week, and \$150 a month) as our primary conditions of interest, and the last two conditions (\$7 a week and \$30 a month) as a robustness check that was conducted simultaneously. Below, we separately report analyses for these two groupings of conditions.

3.1 \$5 Per Day, \$35 Per Week, and \$150 Per Month Conditions

3.1.1. Sign-ups. To examine whether sign-up rates for the recurring deposit program differed as a function of condition, we conducted a logistic regression analysis with dummy-coded condition variables. The omnibus effect of condition was significant, Wald $\chi^2(2) = 361.07$, p < .001. In line with our hypothesis, the more granular the framing, the more users signed up, with 29.9% signing up under the daily framing, 10.3% signing up under the weekly framing, and 7.1% signing up under the monthly framing. Follow-up contrast tests indicated that significantly more users signed up under daily framing compared to weekly framing (B = 1.31, Wald $\chi^2(1)$ = 199.13, p < .001), and significantly more users signed up under daily framing compared to monthly framing (B = 1.72, Wald $\chi^2(1)$ = 258.71, p < .001). Finally, more users signed up under weekly framing compared to monthly framing (B = .41, Wald $\chi^2(1)$ = 11.23, p < .001; See Table

⁴ Acorns also monitored weekly logins, number of weekly withdrawals, and average weekly withdrawal amount, though these variables fell outside the scope of the current research project.

- 2, Model 1). The omnibus effect of condition remained significant when we controlled for income and age (Wald $\chi^2(2) = 362.19$, p < .001), and all contrast tests also remained significant (Bs > .40, ps < .001; See Table 2, Model 2).
- **3.1.2. Retention**. We examined retention over three separate time points: approximately one month after registration, two months after registration, and three months after registration (See Figure 2 for a graphical depiction of results, and Table S2 in the Appendix for full logistic regression results).
- **3.1.2.1. Retention at One Month.** To examine whether retention differed as a function of condition at one month, we conducted a logistic regression analysis with retention as the dependent variable (1 = still enrolled in recurring deposits; 0 = no longer enrolled in recurring deposits) and condition as a dummy-coded variable. The omnibus effect of condition was significant, Wald $\chi^2(2) = 12.46$, p < .001; fewer people remaining enrolled after one month in the daily framing (75%), than in the weekly framing (85%) or monthly framing (86%) conditions. Follow-up contrast tests indicated that significantly more users remained in the weekly framing than the daily framing, (B = .63, Wald $\chi^2(1) = 7.66$, p < .01), and more users remained in the monthly framing than the daily framing (B = .73, Wald $\chi^2(1)$ = 6.77, p < .01), but that there was no difference in retention rates after one month between the weekly and monthly conditions (B = -.10, Wald $\chi^2(1) = 09$, p = .77; Table S2, Model 1). The omnibus effect of condition remained significant when we controlled for income and age (Wald $\chi^2(2) = 8.39$, p = .02), and the significant contrast tests also remained significant (Bs > .53, ps < .05; Table S2, Model 2). Importantly, we note that even despite lower retention rates in the daily versus weekly and monthly conditions after one month, overall participation in the program was still higher in the

daily condition (22%) compared to the weekly (9%) and monthly (6%) conditions ($\chi^2(2, N = 5342) = 249.52, p < .001$).

- 3.1.2.2. Retention at Two Months. To assess retention from one month to two months, we again conducted a logistic regression and found no difference in retention between conditions, Wald $\chi^2(2) = 1.04$, p = .54, with roughly the same percentage of users remaining enrolled in the recurring deposit program from one month to two months: (daily framing: 89%; weekly framing: 89%; monthly framing: 93%; Table S2, Model 3). Results held when we controlled for income and age (Wald $\chi^2(2) = 1.05$, p = .59; Table S2, Model 4).
- 3.1.2.3. Retention at Three Months. Finally, we conducted a logistic regression assessing retention from two months to three months. Again, there were no differences in retention between conditions, Wald $\chi^2(2) = 3.31$, p = .19, with roughly the same percentage of users remaining enrolled in the recurring deposit program from two months to three months: (daily framing: 94%; weekly framing: 92%; monthly framing: 90%; Table S2, Model 5). Results held when we controlled for income and age (Wald $\chi^2(2) = 4.29$, p = .12; Table S2, Model 6).

In short, although retention rates differed as a function of condition after one month, for the remainder of the longitudinal study, they remained consistent across conditions.

3.1.3. Income. We had hypothesized that one reason why a more granular framing would be effective for encouraging enrollment was because giving up small amounts of money on a daily basis might seem less psychologically painful and more feasible than giving up a large amount of money on a monthly (or weekly) basis. The field study context of this study, however, did not allow us to directly investigate perceptions of psychological pain. Nonetheless, if larger, less granular amounts seem more psychological painful and less feasible, then framing recurring deposits in such terms (i.e., in weekly or monthly amounts) should be primarily appealing to

users who have greater financial resources: namely, users who have higher incomes. Thus, we examined whether there were any differences in the decision to enroll in the recurring deposit program as a function of both condition and household income. See Figure 3 for a graphical depiction of results, and Table S3 in the Appendix for full regression table results.

To do so, we conducted a factorial logistic regression with condition and income bracket as dummy-coded categorical between-subjects factors and decision to enroll as the dependent variable, and contrasts capturing differences in sign-ups for pairs of income brackets and pairs of conditions. Household income was bracketed in five bins (1 = less than \$25,000; 2 = \$25,000 - \$49,999; 3 = \$50,000 - \$99,999; 4 = \$100,000 - \$250,000; 5 = more than \$250,000). Because there were so few consumers in the highest income bracket (i.e., \$250,000+; n = 16), we combined this income bracket with the next highest one (i.e., \$100,000 - \$249,999) for this analysis. Doing so, we obtained an overall interaction between condition and income, Wald χ^2 (6) = 33.09, p < .001. Before offering a detailed reporting of this interaction below, we first wish to highlight the main takeaway that arises from this interaction. As shown in Figure 3, consumers in lower income brackets were less likely to sign up for the automatic savings program when it was framed in a less granular way (i.e., as \$150/month or \$35/week). However, when the automatic savings program was framed in the most granular form – that is, as \$5 per day – then there were no differences in sign-up rates across income brackets.

Follow-up interaction tests indicated that there was a difference between sign-ups for the daily versus monthly conditions when comparing the <\$25,000 income bracket to the \$100,000+ income bracket (B = -1.27, Wald $\chi^2(1)$ = 10.00, p < .01). As shown in the rightmost section of Figure 3, under the \$150 per month condition, three times as many consumers in the highest rather than lowest income bracket participated in the program when it was framed as a \$150

monthly deposit (B = 1.21, Wald $\chi^2(1)$ = 13.27, p < .001), but this difference in participation was eliminated when deposits were framed as \$5 per day (see the leftmost section of Figure 3; B = .05, Wald $\chi^2(1)$ = 0.05, p = .82). Likewise, there was a difference in sign-ups for the daily versus monthly conditions when comparing the \$25,000-\$49,999 income bracket against the \$100,000+ income bracket, (B = -1.23, Wald $\chi^2(1)$ = 10.72, p < .001). Again, approximately three times as many consumers in the \$100,000+ rather than the \$25,000-\$49,999 income bracket participated in the program when it was framed as a \$150 monthly deposit (B = 1.14, Wald $\chi^2(1)$ = 13.67, p < .001), but this difference in participation was eliminated when deposits were framed as \$5 per day (B = .09, Wald $\chi^2(1)$ = .17, p = .68). There was not, however, a difference in sign-ups between daily and monthly conditions when comparing the two top income brackets to each other (B = -.32, Wald $\chi^2(1)$ = .75, p = .39.

Similar interactions arose when comparing daily to weekly conditions. Namely, there was a difference between sign-ups for the daily versus weekly conditions when comparing the <\$25,000 income bracket to the \$100,000+ income bracket (B = -.93, Wald $\chi^2(1)$ = 7.40, p < .01): approximately two times as many consumers in the highest rather than lowest income bracket participated in the program when it was framed as a \$35 weekly deposit (B = .88, Wald $\chi^2(1)$ = 11.39, p < .001), but as noted earlier, this difference in participation was eliminated when deposits were framed as \$5 per day (B = .05, Wald $\chi^2(1)$ = 0.05, p = .82). Likewise, there was a difference in sign-ups for the daily versus weekly conditions when comparing the \$25,000-\$49,999 income bracket against the \$100,000+ income bracket, (B = -1.26, Wald $\chi^2(1)$ = 14.51, p < .001). Here, approximately three times as many consumers in the \$100,000+ rather than the \$25,000-\$49,999 income bracket participated in the program when it was framed as a \$35 weekly deposit (B = 1.18, Wald $\chi^2(1)$ = 21.49, p < .001), but this difference in participation was

eliminated when deposits were framed as \$5 per day (B = .09, Wald $\chi^2(1)$ = .17, p = .68). There was not a difference in sign-ups between daily and weekly conditions when comparing the two top income brackets to each other (B = -.45, Wald $\chi^2(1)$ = 1.82, p = .18).

No differences emerged for the weekly versus monthly conditions when comparing the lower income brackets to the highest income bracket (Bs < .33, ps > .43).

Framing deposits in the most granular terms (i.e., in terms of daily amounts), then, seems to reduce the participation gap between lower and higher income individuals in this recurring deposit program.

3.2. \$7 Per Week and \$30 Per Month Conditions

- **3.2.1. Sign-ups**. We again conducted a logistic regression analysis with a dummy-coded independent variable representing condition. In line with our hypothesis, more people signed up under the weekly framing (39.9%) than the monthly framing (21.8%), B = .87, Wald $\chi^2(1)$ = 133.86, p < .001. Results held when we controlled for income and age, B = .91, Wald $\chi^2(1)$ = 141.79, p < .001. (See Table 3 for full logistic regression results).
- **3.2.2. Retention**. As in the analyses for the \$150 conditions, to examine whether retention differed as a function of condition, we conducted a logistic regression analysis with retention as the dependent variable (1 = still enrolled in recurring deposits; 0 = no longer enrolled in recurring deposits) and condition as a dummy-coded independent variable at one month, two months, and three months into the program. See Figure 4 for a graphical depiction of results, and Table S4 in the Appendix for full logistic regression results.
- 3.2.2.1. Retention at One Month. Of the participants who signed up for recurring deposits upon registration, retention rates at one month did not differ as a function of condition, B = .17, Wald $\chi^2(1) = 0.79$, p = .37, with roughly the same proportion of people remaining

enrolled after one month in the weekly framing (87%) and in the monthly framing (89%) conditions. Results held when we controlled for income and age, B = .10, Wald $\chi^2(1) = 0.24$, p = .62.

- 3.2.2.2. Retention at Two Months. A similar pattern was obtained for retention from one month to two months, B = .03, Wald $\chi^2(1) = 0.01$, p = .91, with 94% being retained in both conditions. Results held when we controlled for income and age, B = -.02, Wald $\chi^2(1) = 0.003$, p = .95.
- 3.2.2.3. Retention at Three Months. Finally, a similar pattern was obtained for retention from two months to three months, with 94% being retained in the monthly condition and 95% being retained in the weekly condition, B = -.29, Wald $\chi^2(1) = 0.90$, p = .34. Results held when we controlled for income and age, B = -.33, Wald $\chi^2(1) = 1.20$, p = .27.
- 3.2.3. Income. As in the \$150 conditions, we examined whether there were any differences in the decision to enroll in the recurring deposit program as a function of condition and income bracket. See Figure 5 for a graphical depiction of these results, and Table S5 in the Appendix for full regression table results. Although there was an overall significant interaction between condition and income bracket (Wald $\chi^2(3) = 10.49$, p = .02), follow-up tests indicated that no significant interactions emerged for the weekly versus monthly conditions when comparing the lower income brackets to the highest income bracket (Bs < .28, ps > .27), results that were also found when comparing weekly to monthly framings in the \$150/month conditions. The significant overall interaction arises from an unpredicted (and theoretically less interesting) comparison: there was a difference in sign-ups for the weekly versus monthly conditions when comparing the \$25,000-\$49,999 income bracket against the \$50,000-\$99,999 income bracket, (B = -.59, Wald $\chi^2(1) = 10.43$, p < .001). Here, almost two times more consumers in the \$50,000-

\$99,999 income bracket compared to the \$25,000-\$49,999 income bracket participated in the program when it was framed as a \$30 monthly deposit (B = .80, Wald $\chi^2(1)$ = 33.19, p < .001), but there was only a trend-level difference between these income brackets within the \$7 weekly deposit condition (B = .21, Wald $\chi^2(1)$ = 3.23, p = .07).

4. General Discussion

The fields of marketing and behavioral economics have implemented a variety of solutions to help consumers overcome the many obstacles they face in pursuit of saving for the long term. We add to this growing literature by examining the effectiveness of an intervention meant to encourage the take-up of a recurring deposit program. Namely, we asked new users of a financial tech app whether they wished to sign up for a recurring deposit program, but framed those recurring deposits in more or less granular terms. In a departure from the existing literature on temporal framing of financial outcomes, here we examined consequential decisions in a field setting. In what follows, we first review how enrollment behavior and retention differ as a function of temporal framing. We then discuss whether reframing a recurring deposit saving program in more granular terms may seem psychologically less painful, before closing with a discussion of limitations and future directions.

4.1 Enrollment Behavior

In the three central conditions, we found that take-up was approximately four times higher when deposits were framed in daily terms (i.e., \$5 per day) compared to monthly terms (i.e., \$150 per month), and approximately three times higher when compared to a weekly framing (i.e., \$35 per week). Further, take-up of the recurring deposit program was almost 1.5 times higher when framed in weekly versus monthly terms. We has a consistent basic finding that more granular framing led to higher take-up with two additional, robustness check

conditions that framed deposits in lower overall amounts: take-up was approximately twice as high when deposits were framed as \$7 per week compared to \$30 per month. Taken together, temporally reframing a recurring deposit in a more granular manner led to increased take-up of the program.

It is important to acknowledge that the users who were randomly assigned to the different temporal framing conditions were users who had already decided to make an initial deposit with Acorns. As a result, the overall baseline participation rates in the present study may be inflated relative to what we might observe from a sample of users who had not decided to make an initial deposit. We have no reason to suspect, however, that differences between conditions would be different if we were to have offered the recurring deposit saving program to all users regardless of whether they made an initial deposit. Just the same, future research should implement an experimental design in which all users are offered a recurring deposit program.

4.2 Retention

Due to the longitudinal nature of this study, we were also able to investigate the extent to which the initial framing of recurring deposits prompted continued enrollment in the program. Results indicated that after one month, there was a higher drop-out rate in the daily framing condition compared to the weekly or monthly conditions. Whereas approximately a quarter of the consumers who enrolled in the daily condition ended up dropping out after one month, only approximately 15% dropped out in the weekly and monthly conditions. But, as noted above, due to a large difference in enrollment between conditions, even with this higher drop-out rate in the daily amount condition, there were still more consumers from the daily conditions enrolled in the recurring deposits program after one month (and also for the rest of the program) than for the weekly and monthly conditions. At subsequent periods of 2 and 3 months, retention remained the

same across conditions. It may be the case, then, that a higher proportion of consumers who sign up for a recurring deposit program when it is framed in a granular way regret doing so after a short period of time (i.e., a month). After this time period, however, enrollment remained stable regardless of initial condition.

We also wish to note here that our robustness check conditions that involved much lower amounts of money (\$7 per week and \$30 per month) showed no differences in retention at any of the time periods. Although this higher retention rate is promising, these consumers are clearly depositing much lower amounts of money into their accounts than those in the \$5 per day/\$35 per week/\$150 per month conditions.

4.3 Possible Psychological Mechanisms

4.3.1. Psychological Pain. Drawing on prior work regarding temporal reframing (e.g., Gourville 1999) as well as how consumers view lump sums versus annuitized streams of money (Goldstein et al. 2016), we suggested that one reason why a more granular framing would be effective for encouraging enrollment was because giving up small amounts of money on a daily basis might seem less psychologically painful and more feasible than giving up a large amount of money on a monthly (or weekly) basis. Although the field study context of this study did not allow us to directly probe this psychological mechanism, an analysis of average initial deposit as well as enrollment differences as a function of income provided some compelling indirect evidence for this proposition. Namely, if smaller, more granular amounts do in fact seem less psychologically painful and more feasible than larger, less granular amounts, then framing recurring deposits in terms of smaller, daily deposits should be appealing to consumers across the income spectrum. Likewise, if larger, less granular amounts seem more psychological painful and less feasible, then framing recurring deposits in such terms should be primarily appealing to

a segment with higher income (i.e., a segment that could feasibly make such large deposits). Put differently, signing up for the recurring deposit program when framed in weekly or monthly terms may seem like a more burdensome responsibility, leading to take-up only among consumers who already felt like they had sufficient resources to participate. Indeed, the consumers who participated in the recurring deposit program when it was framed in weekly or monthly terms made higher initial deposits than those who participated when it was framed in daily terms.

More to the point, the recurring deposit program seemed to appeal to a wide set of customers, independent of income, but the weekly and monthly framing only appealed to a segment of higher income customers: as noted above, a significant interaction arose such that when the program was framed as \$150/month, significantly more users signed up from the highest income bracket compared to the lowest income brackets. But, when the program was framed as \$5/day, there were no differences between income brackets. And, similarly, a significant interaction arose such that when the program was framed as \$35/week, significantly more users signed up from the highest income bracket compared to the lowest income brackets. We note, however, that these interactions with income bracket did not arise when making comparisons between the weekly and monthly conditions, both for the \$35 per week condition compared to the \$150 per month condition, and for the \$7 per week compared to \$30 per month condition. It may simply be the case that the daily framing is the most powerful form of granular framing when it comes to reducing the income gap in participation in savings programs.

A major issue that faces policy makers concerns how best to encourage engagement in saving programs across the income spectrum. The results of this work suggest that one way to reduce the income gap in saving behavior is by framing recurring savings programs in a granular,

daily format: not only did this framing encourage more people to save, it may have encouraged those who tend to struggle the most to start saving.

4.3.2. Poor Financial Forecasting. In addition to differences in perceived psychological pain, the more granular framing of saving amounts could have led to higher take-up of the automatic savings program because of poor financial forecasting. It is possible, for example, that consumers made errors when calculating how much \$5 per day really amounted to over time, and thus, underestimated how much they would actually be saving. Notably, we did observe a difference in retention rates between the daily condition and the weekly and monthly conditions at one month into the intervention, suggesting that there was some portion of new users who made a forecasting error when estimating how much they could afford to save (and then corrected this error by dropping out of the program after one month). We note, however, that even once this correction took place, there were still significantly more users enrolled in the automatic deposit program who had initially seen the daily (rather than weekly and monthly) framing.

4.3.3. Different Considerations of Opportunity Costs. Further, temporally reframing monetary amounts may call to mind different sets of opportunity costs for consumers (Spiller 2011). For example, when considering saving \$5 a day, there may be dozens of expenditures that consumers could consider that cost \$5 a day (e.g., a nice coffee, a sandwich, some candy, etc.), but when considering \$150/month, there may be relatively few expenditures that cost this much (e.g., one nice dinner out at a restaurant). As a result, a more granular temporal reframing could suggest to a consumer that even though they may have to give up an expenditure or two, there are still plenty of other items that fall under the umbrella of \$5 per day that could still be purchased. But when considering what would need to be given up to make a \$150 per month

contribution to a saving account, there could be fewer comparisons, leading to an overall sense that a contribution of this magnitude would be more restrictive.

4.4 Limitations and Future Directions

Despite the promise of temporal reframing on encouraging user take-up of recurring deposit programs, we nonetheless acknowledge the limitations of the current research. First, the research was conducted on a self-selected group of users who were already interested in signing up for a financial technology application. We question whether take-up rates would be quite so high in a sample of users who were not already interested in better organizing their finances. But, even though overall take-up rates may be lower in a broader sample, we suspect that the between-group differences in take-up would remain. Future research should thus examine whether more granular framing is similarly effective for a broader, more representative sample.

Along similar lines, we acknowledge here one possible limitation with our experimental design: as noted above, because the initial deposit amounts that were offered to users were a function of their income, we would expect that those with higher income would make a higher initial deposit. Although we do not have any reason to suspect that this initial difference in the deposit amounts would influence the interaction between income bracket and condition on sign-up behavior, future research could use an experimental design in which all users are offered the same options for their initial deposit.

Notably, in the robustness check conditions (i.e., \$7 per week vs. \$30 per month), even though sign-up rates differed, initial deposit amount did not differ as a function of condition and the decision to enroll in the recurring deposit program. We can only speculate as to why we observed such differences in the \$150 per month conditions, and not in the \$30 per month conditions. Again, we treated differences in initial deposits as proxies for differences in how

burdensome the recurring deposit saving programs seemed: the more burdensome the program, the more likely it would be that consumers with higher resources would sign up. Even though it may be the case that \$7 per week seemed more manageable than \$30 per month (as indicated by the higher sign-up rate in the former compared to the latter condition), the overall amount (i.e., \$30 per month) may not have been all that burdensome to begin with. The burden imposed by \$30 per month compared to \$7 per week may have been large enough to result in different sign-up rates, in other words, but not necessarily large enough to then manifest in terms of differences in initial deposits or income bracket. It would thus be prudent for future research to investigate a variety of different recurring deposit amounts to better gauge the boundaries to the effects that were observed in the \$150 per month conditions.

Given that more consumers dropped out of the program after one month in the \$5 per day condition, but not in the \$7 per week condition, future research should also attempt to identify an optimal recurring deposit amount that maximizes overall sign-ups but minimizes drop-outs. Additionally, although we were able to track users for a period of three months, it is possible that retention rates could change over a longer period of time, or one that includes the holiday season or other periods of time when consumers may wish to spend more of their earnings. Future work may thus want to track users over a longer time interval (e.g., a year or longer).

Further, as may be the case with much of the nudging literature, we cannot at this point observe whether the temporal reframing intervention has universally positive effects for all consumers. Although participation in the saving program increased across income brackets as a result of the temporal reframing intervention, doing so may have had unintended consequences: consumers in the lowest income bracket, for example, could have chosen to save money at the expense of paying off high interest. Given that we did not have access to users' other accounts,

we cannot address such unintended consequences in this dataset, but future research should attempt to examine the holistic effects of temporal reframing interventions.

Finally, we opened this paper by noting that more workers today are paid in a granular format (i.e., instead of the traditional monthly paycheck, workers are paid weekly or even daily). Our reason for highlighting the so-called gig economy was to acknowledge that payments and deposits from the financial system do not need to be thought of solely in monthly terms, as they once were. However, an open question not addressed by the current research is whether or not more granular framing of a recurring deposit program would have differential effectiveness for workers who are paid in more versus less granular ways. It could be the case, for example, that workers who are paid on a daily basis would actually be less likely to sign up for a recurring deposit saving program when it was framed in daily terms: five dollars per day may feel like a larger amount to workers paid daily rather than those paid monthly simply because people paid daily may have smaller reference points than those paid monthly. Additionally, it could be the case that workers who are paid in a more granular way also have a better sense of their (limited) budget, and such a perception could affect willingness to participate in the automatic savings program. This conjecture suggests a possible interesting question for future research: could the timing of the temporal reframing intervention itself affect take-up likelihood? If the program is advertised immediately after a worker receives their paycheck, for example, they may perceive more slack in their future budget (Lynch, Spiller, and Zauberman 2015), leading to a greater willingness to participate across temporal reframing conditions; if the program is advertised toward the end of a pay cycle (i.e., when limited budgets are more salient), then the more granular reframing could be more effective. Future research should examine the link between

temporal framing of recurring deposit saving programs, payment frequency, and the timing of such interventions.

4.5 Conclusion

In summary, this field experiment demonstrates the power of temporal reframing to boost participation in a recurring deposit saving program. Among new users of a savings app who had already agreed to make an initial deposit to their saving accounts, we quadrupled the number of recurring savers by framing a recurring deposit program in daily amounts as opposed to monthly amounts. We also increased the number of low-income savers, and showed that daily framing could eliminate the income gap in saving behavior. While automatic enrollment in 401(k)s has been shown to reduce the income gap in saving behavior (Madrian and Shea, 2001), this temporal reframing intervention can reduce savings disparities among workers without access to an employer-provided retirement plan. These results are especially relevant given current trends in the labor market, as a growing percentage of workers are now freelancers and are responsible for their own retirement savings. By better understanding the information and choice architectures that influence financial decision-making, we can improve the design of websites and apps that will play an increasingly important role in shaping the financial future of American workers.

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Table 1

Summary of Conditions, Descriptive Statistics, and Sign-Up Rate

	"\$150	/Month Condi	"\$30/Month Conditions"				
		(n = 5,342)		(n = 3,589)			
Condition	\$5/Day	\$35/Week	\$150/Month	\$7/Week	\$30/Month		
	n = 1,772	n = 1,826	n = 1,744	n = 1,817	n = 1,772		
Mean Age	32.84	32.70	32.80	32.30	32.86		
	(10.41)	(10.47)	(10.23)	(9.69)	(10.16)		
% < \$25,000	25.2%	25.4%	26.4%	25.9%	23.8%		
	(n=446)	(n=463)	(n=460)	(n=470)	(n=422)		
% \$25,000 - \$49,999	37.9%	38.4%	37.8%	37.0%	38.5%		
	(n=672)	(n=702)	(n=659)	(n=672)	(n=683)		
% \$50,000 - \$99,999	29.9%	28.5%	29.0%	29.6%	30.5%		
	(n=529)	(n=521)	(n=506)	(n=537)	(n=541)		
% \$100,000 - \$249,999	6.9%	7.2%	6.5%	7.0%	6.9%		
,	(n=122)	(n=132)	(n=114)	(n=127)	(n=122)		
% \$250,000+	0.2%	0.4%	0.3%	0.6%	0.2%		
•	(n=3)	(n=8)	(n=5)	(n=11)	(n=4)		
Sign-Up Rate	29.9%	10.3%	7.1%	39.9%	21.8%		

Note: Standard deviation of age listed in parentheses. Percent of condition at each income bracket may not total 100% due to rounding.

Table 2

Logistic Regression Predicting Sign-Up Decision, \$5/Day, \$35/Week and \$150/Month Conditions (N = 5,342)

8 8	0 1						,	/
							95% C.I. f	for EXP(B)
	В	S.E.	Wald	Df	Sig.	Exp(B)	Lower	Upper
Model 1								
Condition			361.067	2	.000			
\$5/Day vs. \$150/Month	1.716	.107	258.714	1	.000	5.560	4.511	6.853
\$5/Day vs. \$35/Week	1.310	.093	199.130	1	.000	3.708	3.091	4.448
\$35/Week vs. \$150/Month	.405	.121	11.232	1	.001	1.499	1.183	1.900
Constant	-2.570	.093	760.716	1	.000	.077		
Model 2								
Condition			362.185	2	.000			
\$5/Day vs. \$150/Month	1.720	.107	259.236	1	.000	5.584	4.529	6.884
\$5/Day vs. \$35/Week	1.318	.093	200.498	1	.000	3.736	3.113	4.484
\$35/Week vs. \$150/Month	.402	.121	11.023	1	.001	1.494	1.179	1.894
Age	.002	.004	.358	1	.549	1.002	.994	1.010
Income			12.036	3	.007			
Constant	-2.214	.227	95.095	1	.000	.109		

Note: e^B = exponentiated B; Income coded on a categorical scale in which 1 = less than \$25,000, 2 = \$25,000 - \$49,999, 3 = \$50,000 - \$99,999, 4 = \$100,000+; original logistic regression models specified contrasts between daily and monthly conditions, and weekly and monthly conditions. An additional logistic regression model was conducted to specify the daily versus weekly contrast.

Table 3

Logistic Regression Predicting Sign-Up Decision, \$7/Week and \$30/Month Conditions (N = 3,589)

							95% C.I.for EXP(B)	
	В	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1								
\$7/Week vs. \$30/Month	.866	.075	133.861	1	.000	2.378	2.054	2.754
Constant	-1.278	.058	493.378	1	.000	.278		
Model 2								
\$7/Week vs. \$30/Month	.911	.076	141.867	1	.000	2.487	2.141	2.889
Age	.012	.004	9.035	1	.003	1.012	1.004	1.020
Income			72.87	3	.000	1.477	1.350	1.615
Constant	-2.590	.152	288.816	1	.000	.075		

Note: e^B = exponentiated B. Income coded on a categorical scale in which 1 = less than \$25,000, 2 = \$25,000 - \$49,999, 3 = \$50,000 - \$99,999, 4 = \$100,000+.

Figure 1 Acorns Sign-Up Process and Recurring Deposit Intervention

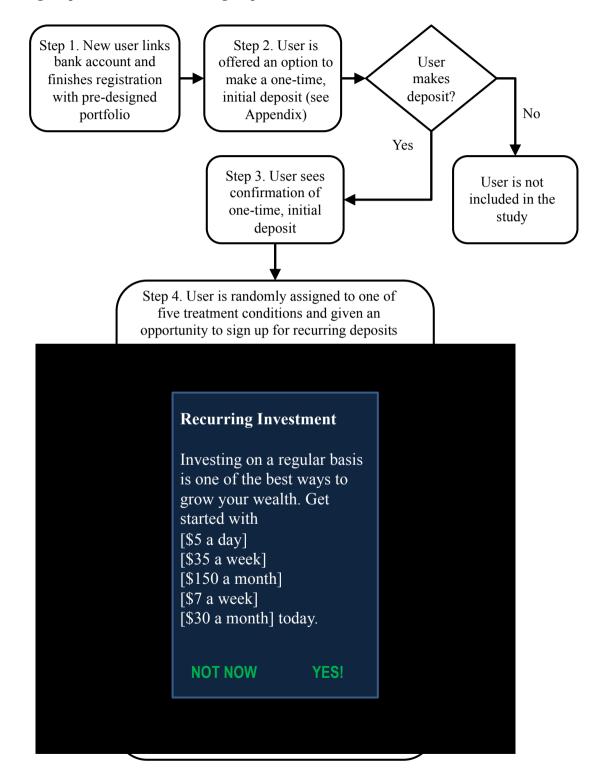
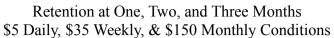


Figure 2



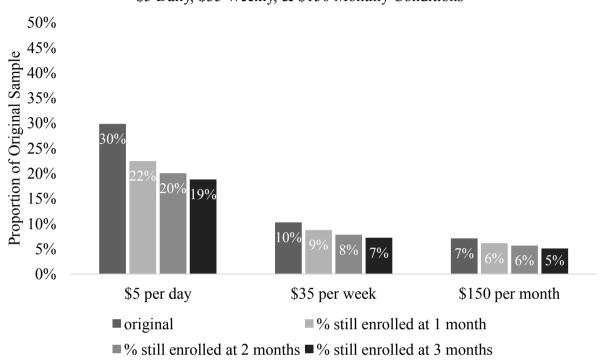


Figure 3

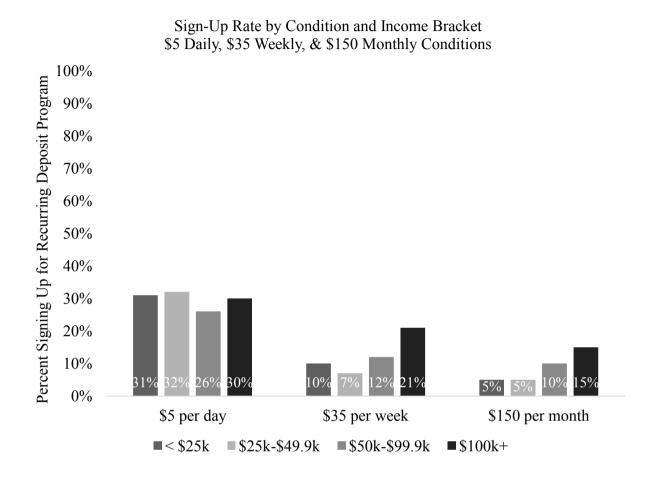
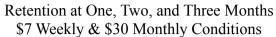
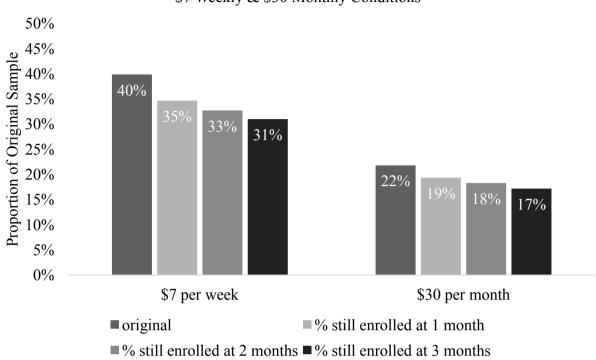
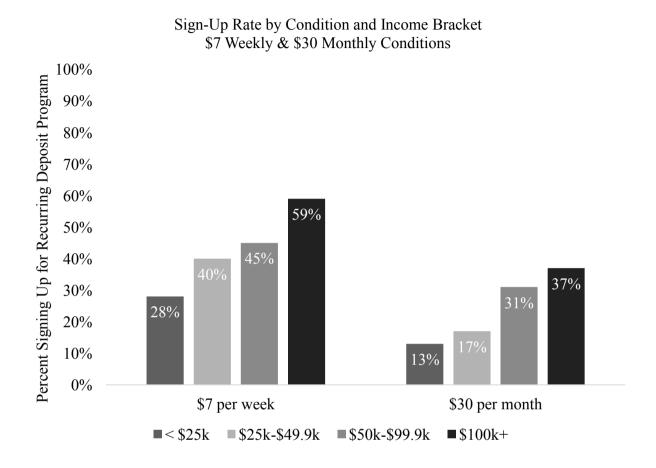


Figure 4







Appendix

1.1. Initial Deposits (\$150/Month Conditions). To complement analyses on income, we examined whether initial deposits differed as a function of condition and the decision to enroll in the recurring deposit program.. To do so, we conducted a univariate ANOVA with two between-subjects factors (condition: daily, weekly, monthly; recurring deposit enrollment: enrolled, not enrolled), and initial deposit as the dependent variable. There were 87 participants who had deposits that were 3 or more standard deviations above the mean. These 87 balances were replaced with the closest nonoutlying value in the sample (Tabachnick & Fidell, 2007).

The univariate ANOVA indicated that there was not a main effect of condition (as noted earlier; F(2, 5326) = .56, p = .57), but that there was a significant main effect of recurring deposit enrollment, (F(1, 5326) = 241.70, p < .001, $\eta_p^2 = .04$), and a significant Condition x Recurring Deposit Enrollment interaction (F(2, 5326) = 71.92, p < .001, $\eta_p^2 = .03$). The nature of this interaction is demonstrated in Figure S1: there are no differences across conditions in initial deposit among those who did not enroll in the recurring deposit program. Among consumers who did enroll, those in the \$35 weekly (winsorized M = \$93.52, SD = \$124.76) and \$150 monthly (winsorized M = \$102.74, SD = \$127.57) conditions did not differ in terms of their initial deposit (t(310) = .63, p = .53), but both had higher initial deposits than those in the \$5 a day condition (winsorized M = \$41.16, SD = \$73.90; ts > 6.84, ps < .001). These results remained significant when we controlled for age and income (ps < .001).

1.2. Initial Deposits (\$30/Month Conditions). We conducted a univariate ANOVA with two between-subjects factors (condition: weekly, monthly; recurring deposit enrollment: enrolled, not enrolled), and initial deposit as the dependent variable. There were 53 participants

who had deposits that were 3 or more standard deviations above the mean. These 53 balances were replaced with the closest nonoutlying value in the sample (Tabachnick and Fidell 2007).

Unlike the \$150 conditions, the univariate ANOVA only indicated a significant main effect for recurring deposit enrollment, $(F(1, 3579) = 47.25, p < .001, \eta_p^2 = .01)$, with those who enrolled in the recurring deposit program having a higher initial deposit (Winsorized M = \$55.86, SD = \$166.59) than those who did not enroll (Winsorized M = \$25.34, SD = \$91.25). There were no other main effects or interactions (ps > .34). Figure S2 provides a graphical representation of these results.

Table S1.

Initial Deposit Options by Income Band

		Income Band		
< \$25,000	\$25,000 -	\$50,000 -	\$100,000 -	\$250,000+
	\$49,999	\$99,999	\$249,999	
\$100	\$250	\$500	\$1,000	\$5,000
\$50	\$100	\$250	\$500	\$1,000
\$20 (default)	\$20 (default)	\$100 (default)	\$100 (default)	\$500 (default)
\$5	\$5	\$20	\$20	\$100
Other amount	Other amount	Other amount	Other amount	Other amount

Logistic Regression Predicting Retention at One, Two, and Three Months, \$5/Day, \$35/Week and \$150/Month Conditions

Table S2.

			<u> </u>			<u> </u>	95% C.I.fo	or EXP(B)
	В	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1 (One Month)								
Condition			12.458	2	.002			
\$5/Day vs. \$150/Month	728	.280	6.774	1	.009	.483	.279	.835
\$5/Day vs. \$35/Week	632	.228	7.658	1	.006	.532	.340	.832
\$35/Week vs. \$150/Month	097	.332	.085	1	.771	.908	.474	1.740
Constant	1.840	.261	49.644	1	.000	6.294		
Model 2 (One Month)								
Condition			8.393	2	.015			
\$5/Day vs. \$150/Month	604	.284	4.527	1	.033	.547	.313	.953
\$5/Day vs. \$35/Week	532	.232	5.253	1	.022	.588	.373	.926
\$35/Week vs. \$150/Month	072	.336	.047	1	.829	.930	.482	1.795
Age	.004	.009	.150	1	.699	1.004	.986	1.022
Income			12.040	3	.007			
Constant	2.739	.618	19.671	1	.000	15.475		
Model 3 (Two Months)								
Condition			1.041	2	.594			
\$5/Day vs. \$150/Month	405	.401	1.016	1	.313	.667	.304	1.465
\$5/Day vs. \$35/Week	019	.303	.004	1	.951	.981	.542	1.778
\$35/Week vs. \$150/Month	386	.448	.742	1	.389	.680	.282	1.636
Constant	2.516	.368	46.844	1	.000	12.375		
Model 4 (Two Months)								
Condition			1.054	2	.590			
\$5/Day vs. \$150/Month	396	.407	.950	1	.330	.673	.303	1.493
\$5/Day vs. \$35/Week	.029	.308	.009	1	.926	1.029	.563	1.882
\$35/Week vs. \$150/Month	425	.451	.888	1	.346	.654	.270	1.582
Age	.022	.015	2.125	1	.145	1.022	.993	1.053
Income			1.259	3	.739			
Constant	2.114	.811	6.794	1	.009	8.280		

Model 5 (Three Months)								
Condition			3.308	2	.191			
\$5/Day vs. \$150/Month	.744	.412	3.258	1	.071	2.104	.938	4.717
\$5/Day vs. \$35/Week	.342	.407	.704	1	.401	1.408	.633	3.129
\$35/Week vs. \$150/Month	.402	.468	.738	1	.390	1.494	.598	3.737
Constant	2.186	.334	42.961	1	.000	8.900		
Model 6 (Three Months)								
Condition			4.289	2	.117			
\$5/Day vs. \$150/Month	.860	.423	4.144	1	.042	2.364	1.033	5.411
\$5/Day vs. \$35/Week	.400	.472	.720	1	.396	1.492	.592	3.760
\$35/Week vs. \$150/Month	.460	.417	1.219	1	.269	1.584	.700	3.584
Age	.000	.017	.001	1	.978	1.000	.967	1.035
Income			4.011	3	.260			
Constant	2.396	.902	7.053	1	.008	10.980		

Note: e^B = exponentiated B. Income coded on a categorical scale in which 1 = less than \$25,000, 2 = \$25,000 - \$49,999, 3 = \$50,000 - \$99,999, 4 = \$100,000+; original logistic regression models specified contrasts between daily and monthly conditions, and weekly and monthly conditions. For presentation purposes, an additional logistic regression model was conducted to specify the daily versus weekly contrast.

Table S3.

Logistic Regression Predicting Sign-Up As a Function of Condition and Income Bracket, \$5/Day, \$35/Week and \$150/Month Conditions

							95% C.I.fe	or EXP(B)
_	В	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Condition Main Effect			8.096	2	.017			
Income Main Effect			20.733	3	.000			
Income x Condition			33.085	6	.000			
Daily vs. Monthly X <\$25k vs. \$25k-\$49.9k	.036	.305	.014	1	.907	1.036	.570	1.885
Daily vs. Monthly X <\$25k vs. \$50k-\$99.9k	.945	.298	10.039	1	.002	2.573	1.434	4.616
Daily vs. Monthly X <\$25k vs. \$100k+	1.265	.400	9.995	1	.002	3.545	1.618	7.768
Daily vs. Monthly X \$25k-\$49.9k vs. \$50k-\$99.9k	.909	.264	11.850	1	.001	2.483	1.479	4.167
Daily vs. Monthly X \$25k-\$49.9k vs. \$100k+	1.230	.376	10.724	1	.001	3.421	1.639	7.142
Daily vs. Monthly X \$50k-\$99.9k vs. \$100k+	.320	.370	.751	1	.386	1.378	.667	2.844
Daily vs. Weekly X <\$25k vs. \$25k-\$49.9k	.036	.305	.014	1	.907	1.036	.570	1.885
Daily vs. Weekly X <\$25k vs. \$50k-\$99.9k	483	.251	3.699	1	.054	.617	.377	1.009
Daily vs. Weekly X <\$25k vs. \$100k+	.931	.342	7.401	1	.007	2.537	1.297	4.962
Daily vs. Weekly X \$25k-\$49.9k vs. \$50k-\$99.9k	.909	.264	11.850	1	.001	2.483	1.479	4.167
Daily vs. Weekly X \$25k-\$49.9k vs. \$100k+	1.261	.331	14.505	1	.000	3.530	1.845	6.757
Daily vs. Weekly X \$50k-\$99.9k vs. \$100k+	.448	.332	1.822	1	.177	1.565	.817	2.999
Weekly vs. Monthly X <\$25k vs. \$25k-\$49.9k	.366	.348	1.104	1	.293	1.442	.729	2.854
Weekly vs. Monthly X <\$25k vs. \$50k-\$99.9k	.462	.334	1.910	1	.167	1.587	.824	3.055
Weekly vs. Monthly X <\$25k vs. \$100k+	.334	.423	.624	1	.429	1.397	.609	3.203
Weekly vs. Monthly X \$25k-\$49.9k vs. \$100k+	.096	.304	.100	1	.752	1.101	.607	1.996
Weekly vs. Monthly X \$25k-\$49.9k vs. \$100k+	032	.400	.006	1	.937	.969	.443	2.121
Weekly vs. Monthly X \$50k-\$99.9k vs. \$100k+	127	.387	.108	1	.742	.880	.412	1.881
Within Daily Condition								

<\$25k vs. \$25k-\$49.9k	071	.276	.067	1	.796	.931	.543	1.598
<\$25k vs. \$50k-\$99.9k	.250	.142	3.084	1	.079	1.283	.971	1.695
<\$25k vs. \$100k+	.051	.222	.053	1	.818	1.052	.682	1.625
\$25k-\$49.9k vs. \$50k-\$99.9k	624	.231	7.322	1	.007	.536	.341	.842
\$25k-\$49.9k vs. \$100k+	.087	.213	.166	1	.684	1.091	.718	1.657
\$50k-\$99.9k vs. \$100k+	198	.220	.814	1	.367	.820	.533	1.262
Within Weekly Condition								
<\$25k vs. \$25k-\$49.9k	.295	.213	1.912	1	.167	1.342	.884	2.038
<\$25k vs. \$50k-\$99.9k	234	.207	1.272	1	.259	.792	.527	1.188
<\$25k vs. \$100k+	880	.261	11.385	1	.001	.415	.249	.692
\$25k-\$49.9k vs. \$50k-\$99.9k	528	.198	7.137	1	.008	.590	.400	.869
\$25k-\$49.9k vs. \$100k+	-1.175	.253	21.494	1	.000	.309	.188	.508
\$50k-\$99.9k vs. \$100k+	646	.248	6.768	1	.009	.524	.322	.853
Within Monthly Condition								
<\$25k vs. \$25k-\$49.9k	071	.276	.067	1	.796	.931	.543	1.598
<\$25k vs. \$50k-\$99.9k	696	.262	7.034	1	.008	.499	.298	.834
<\$25k vs. \$100k+	-1.214	.333	13.272	1	.000	.297	.154	.571
\$25k-\$49.9k vs. \$50k-\$99.9k	624	.231	7.322	1	.007	.536	.341	.842
\$25k-\$49.9k vs. \$100k+	-1.143	.309	13.674	1	.000	.319	.174	.584
\$50k-\$99.9k vs. \$100k+	519	.297	3.046	1	.081	.595	.332	1.066
Constant	-1.735	.256	46.035	1	.000	.176		
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Note: e^B = exponentiated B. Original logistic regression models specified contrasts between daily and monthly conditions, and weekly and monthly conditions, and \$100k+ bracket versus other brackets. For presentation purposes, additional logistic regression models were conducted to specify the remaining contrasts.

Logistic Regression Predicting Retention at One, Two, and Three Months, \$7/Week and \$30/Month Condition

Table S4.

							95% C.I.f	or EXP(B)
	В	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Model 1 (One Month)								
\$7/Week vs. \$30/Month	174	.196	.789	1	.374	.840	.572	1.234
Constant	2.077	.162	164.760	1	.000	7.977		
Model 2 (One Month)								
\$7/Week vs. \$30/Month	098	.199	.241	1	.623	.907	.614	1.340
Age	.019	.011	3.280	1	.070	1.020	.998	1.041
Income			10.570	3	.014			
Constant	1.996	.580	11.854	1	.001	7.356		
Model 3 (Two Months)								
\$7/Week vs. \$30/Month	033	.292	.013	1	.910	.968	.546	1.714
Constant	2.836	.236	144.381	1	.000	17.053		
Model 4 (Two Months)								
\$7/Week vs. \$30/Month	.017	.295	.003	1	.954	1.017	.571	1.812
Age	.028	.017	2.693	1	.101	1.028	.995	1.063
Income			1.991	3	.574			
Constant	2.555	.906	7.945	1	.005	12.871		
Model 5 (Three Months)								
\$7/Week vs. \$30/Month	.285	.301	.895	1	.344	1.330	.737	2.400
Constant	2.721	.231	138.966	1	.000	15.200		
Model 6 (Three Months)								
\$7/Week vs. \$30/Month	.331	.303	1.196	1	.274	1.393	.769	2.523
Age	.016	.017	.871	1	.351	1.016	.983	1.050
Income			1.729	3	.631			
Constant	2.084	.820	6.467	1	.011	8.039		

Note: e^B = exponentiated B. Income coded on a categorical scale in which 1 = less than \$25,000, 2 = \$25,000 - \$49,999, 3 = \$50,000 - \$99,999, 4 = \$100,000+.

Table S5.

Logistic Regression Predicting Sign-Up As a Function of Condition and Income Bracket, \$7/Week and \$30/Month Conditions

						_	95% C.I.for EXP(B)	
	В	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Condition Main Effect	.878	.251	12.199	1	.000	2.406	1.470	3.939
Income Main Effect			69.186	3	.000			
Income x Condition			10.487	3	.015			
Weekly vs. Monthly X <\$25k vs. \$25k-\$49.9k	251	.219	1.322	1	.250	.778	.507	1.194
Weekly vs. Monthly X <\$25k vs. \$50k-\$99.9k	.334	.217	2.357	1	.125	1.396	.912	2.138
Weekly vs. Monthly X <\$25k vs. \$100k+	.059	.307	.036	1	.849	1.060	.581	1.936
Weekly vs. Monthly X \$25k-\$49.9k vs. \$50k- \$99.9k	.585	.181	10.426	1	.001	1.795	1.259	2.561
Weekly vs. Monthly X \$25k-\$49.9k vs. \$100k+	.310	.283	1.203	1	.273	1.363	.784	2.373
Weekly vs. Monthly X \$50k-\$99.9k vs. \$100k+	275	.282	.954	1	.329	.759	.437	1.319
Within Weekly Condition								
<\$25k vs. \$25k-\$49.9k	538	.129	17.269	1	.000	.584	.453	.753
<\$25k vs. \$50k-\$99.9k	749	.134	31.028	1	.000	.473	.364	.616
<\$25k vs. \$100k+	-1.289	.200	41.608	1	.000	.275	.186	.408
\$25k-\$49.9k vs. \$50k-\$99.9k	211	.117	3.232	1	.072	.810	.644	1.019
\$25k-\$49.9k vs. \$100k+	752	.189	15.849	1	.000	.472	.326	.683
\$50k-\$99.9k vs. \$100k+	541	.192	7.914	1	.005	.582	.399	.849
Within Monthly Condition								
<\$25k vs. \$25k-\$49.9k	286	.176	2.641	1	.104	.751	.532	1.061
<\$25k vs. \$50k-\$99.9k	-1.082	.171	40.102	1	.000	.339	.242	.474
<\$25k vs. \$100k+	-1.348	.233	33.435	1	.000	.260	.164	.410
\$25k-\$49.9k vs. \$50k-\$99.9k	796	.138	33.185	1	.000	.451	.344	.591
\$25k-\$49.9k vs. \$100k+	-1.062	.210	25.484	1	.000	.346	.229	.522
\$50k-\$99.9k vs. \$100k+	266	.206	1.665	1	.197	.767	.512	1.148

Constant -.532 .184 8.375 1 .004 .588

Note: e^B = exponentiated B. Original logistic regression models specified contrasts between \$100k+ bracket versus other brackets. For presentation purposes, additional logistic regression models were conducted to specify the remaining contrasts.

Figure S1.

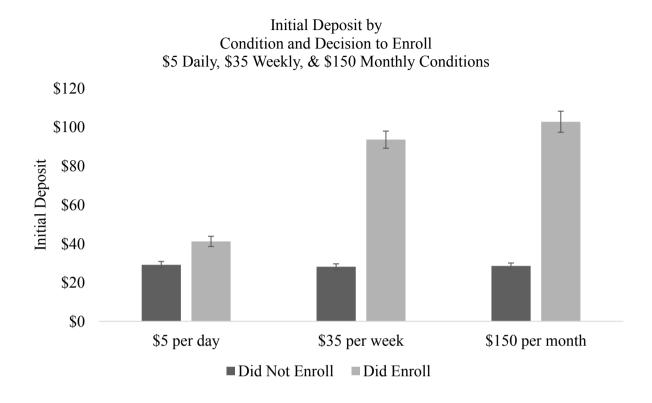


Figure S2.

