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ABSTRACT

Deciding how much to save for retirement can be complicated. Drawing on a field experiment conducted with the Department of Defense, we study whether such complexity depresses participation in an employer-sponsored retirement saving plan. We find that simplifying one dimension of the enrollment decision, by highlighting a potential rate at which non-participants might contribute, increases participation in the plan. Similar communications that did not include a highlighted rate yield smaller effects. The results highlight how reducing complexity on the intensive margin of a decision (how much to contribute) can affect extensive margin behavior (whether to contribute at all) in a setting of policy interest.

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A randomized controlled trials registry entry is available at
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I. Introduction

Deciding how much to save for retirement is a complicated task. For the approximately two-thirds of Americans whose employer offers a retirement savings plan like a 401(k) or 403(b), employees must decide not only whether to participate in the plan, but also how much to save and in which plan fund to invest – decisions that are frequently complicated by uncertainty over future expenses, the timing of retirement, and even the nature of one's own risk or time preferences. Especially for employees who lack financial sophistication, the effort needed to resolve these uncertainties is often significant.

In this paper, we investigate whether the complexity of the retirement savings decision depresses participation in retirement savings plans. One might not expect that uncertainty over whether one's optimal contribution rate is, say, 3% versus 4% would cause one to contribute 0% (i.e., to end up not participating). However, if enrolling in a plan requires deciding how much to contribute, and if making that decision requires incurring costly mental effort or other decision costs, individuals may choose not to participate altogether. Understanding how such complexity shapes retirement saving decisions sheds light on existing barriers to retirement saving as well as on the potential for low-cost interventions to advance the policy goal of higher saving rates.

To study whether decision complexity affects whether employees contribute to their employer-sponsored retirement plans, we analyze the results of a field experiment conducted by the U.S. Department of Defense (DOD). The experiment involved the roughly 300,000 active duty U.S. Army servicemembers who were not enrolled in the Thrift Savings Plan (TSP), the defined contribution portion of the retirement plan the U.S. government offers to its employees. This sample population is young, less educated (most have only a high school degree), racially diverse, and is a group for whom low saving rates are a source of significant policy concern (e.g., Maldon Jr et al. (2015); DOD (2019)). The DOD randomly assigned a subset of these individuals to receive a one-time email that provided information about how to enroll in the TSP and encouraged them to join. For some individuals, the email also attempted to reduce the complexity of the savings decision by highlighting a random specific rate (i.e., 1%, 2%, ...8%) at which the individual could choose to contribute. Highlighting a specific contribution rate might simplify the savings decision if it narrows the range of contribution rates one must consider when deciding whether and how much to save. A final group of individuals were randomly assigned to a control group that did not receive any email. To study the effect of the intervention on behavior, we link experimental group assignment to administrative data on TSP contributions during the subsequent two years.

Our results provide some of the first causal evidence that the complexity of the retirement savings decision contributes to non-participation in employer-sponsored savings plans. In particular, our experimental design enables us to distinguish the effects of providing specific contribution rates from general encouragement to contribute. Relative to the control group, the increase in participation among individuals who received an email that highlighted a specific contribution rate was significantly larger than the increase among those who received the baseline email with no specific rate. In particular, the baseline treatment increased participation by 0.4 percentage points whereas the specific rate treatment increased participation by 0.7 percentage points in the quarter following the intervention, on a base of 2.7 percentage points. The difference in the estimated effects between the two types of emails suggests that at least part of the overall observed effect stems from highlighting a specific contribution rate rather than simply encouraging enrollment. In addition, the observed differences in participation rates across the treatment and control groups largely persist over the two-year window that we study, suggesting the experimental treatment did not simply speed up the timing of enrollment, but rather encouraged new enrollees who would otherwise not have participated (at least over the time horizon we observe). Although these effects are modest in magnitude, it is important to note that the baseline participation rate in our control group was quite low; by construction, our sample population had not enrolled in TSP despite being eligible to do so for an average of six years. In percent terms: the baseline and specific rate treatment groups led to participation increases of 15% and 26%, respectively.

Finally, our estimates reflect an intent-to-treat – if only a small fraction of individuals actually read our communications (as prior literature suggests may be the case), our estimates imply a large behavioral change among that group.

We present two additional findings that are consistent with our interpretation that the intervention increased TSP participation by reducing the complexity of the savings decision. First, if highlighting a specific contribution rate induced certain individuals to enroll by reducing the complexity of the savings decision (as we hypothesize), then the amount these individuals contribute should be concentrated at the highlighted rate. Consistent with this hypothesis, we find that individuals assigned to a specific rate treatment were not only more likely to contribute, they were more likely to contribute at exactly the highlighted rate. Second, although enrolling in the TSP requires individuals to actively select their desired contribution rate, they need not actively select a fund allocation; rather, enrollees who do not select a fund allocation are defaulted into a government securities investment fund. If those individuals who enroll only after receiving a specific rate treatment were actively selecting a non-default fund allocation, it might suggest that decision complexity was not the primary barrier to their participation. However, we find that the effect of the specific rate treatments on contributions is limited to this default fund, consistent with a "path of least resistance" explanation for retirement savings decisions proposed in Choi et al. (2006).

We make several contributions. First, our results demonstrate the potential of very low-cost interventions to improve the performance of efforts designed to increase retirement savings. The small wording changes we study – adding a sentence to an email that highlights a specific contribution rate – entails minimal costs but yields large percentage increases in retirement plan participation from a population that has consistently been resistant to such efforts. To the extent that increased TSP participation by this population is welfare-enhancing, as many policy-makers have expressed their belief to be, including such language constitutes a practical and cost-effective method for increasing plan enrollment – one that is easily implemented by plan administrators in both the public and private sectors.

Second, we contribute to a growing literature that investigates how the complexity of retirement saving decisions shapes behavior. For example, Sethi-Iyengar, Huberman and Jiang (2004) observe a negative correlation between the quantity of fund choices offered by employer-sponsored retirement plans and plan participation by employees, consistent with a model of "choice overload." In a similar spirit, Choi, Laibson and Madrian (2009) and Beshears et al. (2013) find that providing employees with an expedited process for enrolling in their employer's 401(k) plan at a single, employer-specified contribution rate increases plan participation. Like the intervention we study, this "quick enrollment" process was designed to reduce the complexity of the enrollment decision by collapsing a complicated, multi-dimensional choice (e.g., how much to save, which investment plan to select) to a binary one (whether or not to enroll at some prescribed rate). We build on these studies in two main ways. First, our randomized design allows us to more confidently establish the causal link between the interventions we study and the change in savings behavior. Second, unlike Choi, Laibson and Madrian (2009) and Beshears et al. (2013), our study design allows us to distinguish the effect of simplifying the enrollment decision by highlighting a specific contribution rate from the effects of simplifying the enrollment process itself (i.e., replacing the standard enrollment form) and/or reminding employees to enroll – mechanisms that may exert an independent effect on plan participation. This distinction is important both theoretically – e.g., for assessing the extent to which simplifying one component of a multi-dimensional decision affects decision-makers' willingness to engage with the decision at all – as well as practically – e.g., for assessing the potential efficacy of alternative policies.

Our analysis is particularly related to two recent studies. First, our study design is closely related to Choi et al. (2017), who show that including contribution rate "anchors" in written communications to current plan participants can draw participant contributions toward the anchored rate. We build on that analysis by focusing on a different population (non-participants as opposed to current plan members) and a different outcome (plan participation versus contribution rate selection). These differences are important because plan participants and non-participants are likely to vary in significant ways from one another and the role of decision costs may differ between them. Indeed, understanding the factors that can help overcome barriers to savings plan participation is of particular policy interest, given prior evidence of the role that habit formation plays in saving behavior (Loibl, Kraybill and DeMay, 2011) and the fact that major public policy efforts worldwide focus on a "foot in the door" approach to increasing savings (e.g., CFPB (2020), KiwiSaver Act of 2006).

Blumenstock, Callen and Ghani (2018) also provide experimental evidence on the role of complexity in savings decisions. Studying participation in an employee savings program in Afghanistan, they find that providing financial counseling about various saving options caused more employees to switch from their current contribution rate than did a simple reminder about the availability of the savings plan. Our findings complement this study in several ways. First, we provide additional support for the importance of decision costs as an impediment to savings plan participation from a dramatically different societal and institutional context. Second, like Choi et al. (2017), Blumenstock, Callen and Ghani (2018) focus their analysis on changes in plan contributions – which may reflect either extensive- or intensive-margin changes in participation; in contrast, for the reasons noted above, we focus on decision costs as a barrier to plan participation.[1] Finally, although the estimated effect of the financial consultations is larger than the estimated effect of our intervention, the consultations are also substantially more resource-intensive; our results highlight the potential for resource-constrained employers or governmental agencies to reduce decision costs through lighter-touch interventions as well.

Outside of the retirement savings context, a number of papers have studied how providing a suggested donation amount shapes charitable contributions. The question is analogous to ours; highlighting a specific donation amount can reduce decision costs for the donor by narrowing the range of options one must consider. Edwards and List (2014) find that

[1] Indeed, the results reported in Blumenstock, Callen and Ghani (2018), Online Appendix Table A17, suggest that the vast majority of the contribution changes induced by the financial consultation they study were among current plan participants.

highlighting a specific charitable contribution amount increases the likelihood of making a charitable donation, whereas Altmann et al. (2019) find no evidence along these lines. In addition, Altmann et al. (2019) find that the magnitude of a charitable donation default affects the likelihood and amount of donation. This related question – how the magnitude of a highlighted rate affects contributions – has been studied in the retirement savings context by Choi et al. (2017), Beshears et al. (2017), Choukhmane (2019), and in a companion piece to the current paper, Goldin, Homonoff and Tucker-Ray (2017).[2] In contrast, the present results highlight how reducing complexity on the intensive margin of a decision (how much to contribute) can affect extensive margin behavior (whether to contribute at all).

This paper is organized as follows. Section II reviews the institutional background on federal government retirement savings plans. Section III describes the experiment and our sample. Section IV describes the data sources used in the empirical analysis. Section V presents the results. Section VI concludes.

II. Institutional Background

All U.S. federal government employees – both civilian and military – are eligible to contribute to the Thrift Savings Plan (TSP), the federal government's defined contribution plan. The TSP is similar to a 401(k) plan that might be offered by a private employer. It allows participants to save for retirement at tax-advantaged rates, under either a Roth or traditional retirement savings plan design. Employees who enroll in the TSP select an integer contribution rate, which corresponds to the fraction of their pay that is directed to their TSP account each pay period.[3] After enrolling, the TSP establishes an account for new participants and they subsequently select the investment fund(s) to which they would like to contribute; those who do not select a fund are defaulted into the Government Securities Investment Fund (the

[2] Specifically, Goldin, Homonoff and Tucker-Ray (2017) explore differences in the effect of highlighting low versus high contribution rates on retirement savings during the first month after the intervention.

[3] During our sample period, servicemembers enrolled in the TSP using a form that restricted contribution amounts to percentages of pay. Beginning in January 2019, servicemembers enrolled with a new form that permitted dollar or percentage of pay contributions.

"G" Fund) - a low risk, low return fund of short-term government securities.

At the time of our intervention in 2016, 87 percent of civilian federal employees participated in the TSP, whereas only 43 percent of military servicemembers did so. The difference in enrollment rates between civilian and military employees may be due in part to different saving preferences between the two groups. However, there were also important differences in how the TSP was administered to these two groups of federal employees at the time. First, like many 401(k) plans offered by private employers, the TSP included an employer match for participating civilian employees that was not available to military servicemembers. Second, servicemembers were required to actively enroll in the plan in order to participate, whereas civilian federal employees were automatically enrolled in the TSP unless they actively declined to participate.[4] Finally, during our sample period, servicemembers are eligible for a more generous defined benefit pension than their federal civilian counterparts, with annual benefit equal to at least 50% of the servicemember's three highest salary years. However, most servicemembers never become eligible for these benefits; the pension uses "cliff-vesting" at 20 years of service. Fewer than 20% of servicemembers reach this tenure (GAO, 2019), with even lower rates among Army servicemembers (Maldon Jr et al., 2015).

The low rate of retirement savings among military servicemembers makes this population particularly relevant for studies of the type we conduct.[5] Although our sample differs in important ways from the overall population of individuals covered by employer-provided retirement plans, we are not aware of factors that would limit the applicability of our findings to other populations with similar characteristics.

An important feature of our setting is the lack of an employer-match for TSP contributions during our sample period. On the one hand, this could limit the generalizability of

[4] As of January 1, 2018, the military moved to a Blended Retirement System (with defined benefit and defined contribution components) in which newly hired servicemembers were automatically enrolled in the TSP and all servicemembers are eligible for a 3% match. Our sample period precedes this policy change.

[5] Increasing savings among this population has been a stated goal and focus of Presidential and Congressional commissions (Maldon Jr et al., 2015), the Department of Defense (DOD, 2019), as well as the Consumer Financial Protection Bureau, the Federal Retirement Thrift Investment Board, and military trade groups.

our results to plans that do incorporate a match and which, as a result, may have higher participation rates than our sample. On the other hand, the lack of a match offers two advantages. First, there are significant ethical concerns with interventions that would likely cause some employees to select low contribution rates that entail foregoing some or all of an employer match. Second, matches could focus potential enrollees on the specific contribution rate that maximizes the match, which might obscure precisely the effect we aim to study.

III. Sample and Research Design

Our sample includes the universe of active-duty servicemembers in the U.S. Army who had not contributed to a TSP account in the six years prior to the intervention (January 2010 - January 2016). Members of the experimental sample were assigned to one of 10 experimental groups based on the eighth digit of their social security number (SSN).[6] On January 27, 2016, individuals assigned to one of the treatment groups received an email from the Defense Financing and Accounting Services (DFAS) – the agency within DOD that administers military payments. The email informed individuals that they were not currently enrolled in the TSP and encouraged them to sign up (Appendix Figure A.1a).[7] Since DFAS routinely emails notifications regarding servicemembers' pay, leave, and other human resources information, this form of communication was not out of the ordinary.

Individuals with an SSN ending in 90-99 received the email described above with no additional information (our baseline treatment group). Individuals with an SSN ending in 10-89 (our specific rate treatments) received a version of the email that was identical to that received by the baseline group but for the addition of one sentence: "Many servicemembers

[6]The last four digits of SSNs are randomly assigned. However, a potential concern with this approach to treatment assignment is that the treatment effect may be confounded if other experiments were assigned in the same way (SBST, 2015). Assigning treatment status based on servicemembers' 8th SSN digit was intended to alleviate this concern.

[7]The baseline message included in these emails was created based on the results of a prior field experiment involving this population, conducted in May of 2015. The returns mentioned in this message are based on the rate of return of the C-Fund, the SP 500 index equivalent available to TSP participants. See SBST (2015) and Benartzi et al. (2017) for details.

like you start by contributing at least X% of their basic pay into a Traditional or Roth TSP account." Individuals within the specific rate group were presented with a contribution rate corresponding to the second to last number in their SSN. For example, those with an SSN ending in 10-19 were shown the lowest highlighted rate of 1 percent, while individuals with an SSN ending in 80-89 were shown the highest highlighted rate of 8 percent (see Appendix Figure A.1b for an example).[8] Individuals with an SSN ending in 00-09 were assigned to the control group and did not receive any additional communications from DFAS.

IV. Data

As described above, inclusion in our experimental population is based on lack of prior TSP enrollment. Roughly 60 percent of all Army servicemembers had not enrolled in the TSP prior to the start of our intervention, leaving a sample population of 291,552 non-enrolled active-duty servicemembers. We link administrative data on our population from three sources: payroll data, retirement account data, and Army personnel data.

Our data on TSP participation comes from DFAS payroll data, supplemented with retirement account data from the Federal Retirement Thrift Investment Board (FRTIB), which administers the TSP. These data include monthly contributions to traditional and Roth retirement accounts for the two years after the start of our intervention.[9] The data also include monthly compensation data such as base pay and hazardous duty incentive pay.[10] Unfortunately, the data do not include information on the intermediate outcome of whether servicemembers opened or otherwise engaged with the email communication. In addition, the data do not include information about non-TSP forms of savings, although Skimmyhorn (2016) finds that other retirement savings accounts are uncommon for military members.

[8] Among contributing service members in our data, 34% contribute 8% or more of base pay to the TSP.

[9] We limit our follow-up period to this time period so our results are not conflated with responses to the legislative changes to the TSP enrollment process and match policies implemented at the start of 2018. Contributions to traditional accounts that are made from combat pay are tax-exempt and not subject to normal contribution limits.

[10] Individuals make separate TSP contribution decisions for base pay and hazardous duty incentive pay. We include contributions to special pay in total contributions but only use contributions to base pay in calculating percent contributions.

We complement this data set with retirement account data from the Federal Retirement Thrift Investment Board (FRTIB), which administers the TSP. This data contains quarterly account level records for the two years after our intervention. The data contains similar information to that provided by DFAS, but differs on a few key dimensions. Rather than TSP contribution rate selection, the FRTIB data includes information on the dollar amount contributed to TSP each quarter. For this reason, and since the FRTIB data is reported quarterly rather than monthly, we rely on the DFAS data for our estimates of TSP participation and contribution rate selection. However, unlike with the DFAS data, these data allow us to calculate exact retirement savings balances. Additionally, the FRTIB data include information on fund allocations. TSP has several index funds from which to choose including: government securities (G), fixed-income (F), common stock (C), small capitalization stock (S), international stock (I), and lifecycle funds (L, a combination of the other five funds).[11]

Finally, our administrative personnel data come from the Department of the Army. These data are reported as of January 2016 and include demographic information (i.e., age, gender, race, marital status, number of children), service and performance information (years of service and rank), and measures of human capital (education level and Armed Forces Qualification Test (AFQT) scores). This data set also includes information on whether a servicemember left the Army during our study period. It is common for the Army to experience high turnover rates – roughly 29 percent of our sample has left the Army by the end of our two-year follow-up period. For long-run outcomes we exclude individuals who have left the Army prior to the period being analyzed.[12]

Table 1 provides summary statistics of the demographic characteristics of our study sample. The majority of our sample are enlisted servicemembers (84 percent) with an average age of 27 years old at the start of our intervention. These individuals have been in the military

[11] The G-Fund is a Government Bonds Fund. The F-Fund is a fixed income fund and includes an index of corporate bonds. The C-fund is an index fund managed to replicate the S&P 500 Index. The S-Fund is a small cap fund managed to match the Dow Jones U.S. Completion Total Stock Market Index. The I-Fund is an International Fund designed to match the MSCI EAFE international Index. The L-Fund includes several TSP lifecycle fund options.

[12] Analyses in Section V demonstrate that our results are not sensitive to this restriction.

for an average of six years, suggesting that they had several opportunities to enroll in TSP prior to our intervention. The majority are male (87 percent) and just over half are married with an average of one child. A majority (57 percent) of the sample population is white, 21 percent are black, 15 percent are Hispanic, and 7 percent identify as another race or ethnicity. Most individuals in our sample have a high-school diploma or GED (69 percent), but only 18 percent have completed a bachelors degree or above.[13] The average individual earns $3,000 per month ($36,000 per year) in base pay, plus additional compensation in forms such as housing and meal allowances.[14]

This table also explores whether the treatment assignment mechanism generated groups that are balanced across our demographic characteristics. Column 4 presents results of an F-test for equality across our three main experimental groups – those receiving no email, those receiving the baseline email, and those receiving any one of the specific rate emails. The results are consistent with random treatment group assignment.

V. Results

In our primary analysis, we look separately at the effect of receiving the baseline email and the effect of receiving an email that highlighted a specific rate on retirement savings outcomes. In most of our analyses of TSP participation and percent contributions, we collapse monthly data to the quarter level keeping the maximum contribution rate in the three-month period.[15] Our main econometric model is:

$$Y_{it} = \beta_0 + \beta_1 Baseline_i + \beta_2 Specific\,Rate_i + \beta_3 X_i + \varepsilon_{it} \quad (1)$$

where Y_{it} is a savings outcome for individual i at follow-up period t, and X_i is a vector of individual-level baseline characteristics including age, sex, race, marital status, education,

[13]The remaining 13 percent of the sample have completed some college.

[14]See www.goarmy.com/benefits/total-compensation

[15]Since very few individuals change their contribution rate selection within the quarter, our results are substantively unchanged if instead we use their first contribution rate selection.

AFQT score, years of service, and enlisted status. $Baseline_i$ is an indicator for being assigned to receive the baseline email and $Specific\ Rate_i$ is an indicator for receiving one of the eight email communications that highlighted a specific contribution rate (i.e., 1%, 2%, ..., 8%). Therefore, β_1 and β_2 compare the savings behavior of individuals who received either the baseline email or specific rate emails, respectively, to individuals who received no experimental communications from DFAS.

Effects of Treatment on TSP Participation

We begin by estimating the effects of the intervention on savings behavior at the end of the first quarter post-intervention. The first two columns of Table 2 present estimates for the effect of the two communication types (baseline and specific rate) on the likelihood of participating in TSP, with and without demographic controls. Column 1 shows that the baseline email led to a statistically significant increase of 0.42 percentage points in the participation rate. Although this treatment effect is modest when evaluated as a share of the overall sample, if readership rates for the communications are low in this sample population – as prior studies have suggested – it may nonetheless represent a substantial change in behavior among the sub-population of servicemembers who read the email.[16] Additionally, the participation rate among the control group is quite low – only 2.7 percent of control group members enrolled in TSP in the first quarter of our intervention. Therefore, the baseline email led to a 15 percent increase in the likelihood of participating in TSP.

The second row of column 1 shows the effect of receiving an email that also highlighted a specific rate. That treatment increased the probability of contribution by 0.71 percentage points (26%). The specific rate effect is nearly twice as large as the baseline effect and the difference is statistically significant at the 1% level. Column 2 includes the individual controls described above and shows that the treatment effects are unchanged, consistent with

[16]For example, Castleman, Patterson and Skimmyhorn (2019) find that fewer than 6% of active-duty enlisted Army servicemembers opened an email sent from DOD regarding participation in an interest rate protection program. Similarly, Castleman et al. (2019) find that 2-3 percent of servicemembers who received communications about transferring their GI-Bill benefits clicked on an email link.

our randomized design.[17]

Columns 3 and 4 present results of the effect of the communications on the average contribution rate (i.e., the fraction of basic pay income an individual contributes to the TSP accounts), again, both with and without demographic controls. Since the overall participation rates in this population are quite low since non-participation in TSP was a requirement to be included in the study, the average contribution rate is also low. Among control group members, the average contribution rate was 0.23 percent. However, as with our extensive margin results, we find that the baseline email and the specific rate emails led to significant increases in the average contribution rate. Specifically, Column 3 shows that the baseline email led to an increase of 0.032 percentage points while the specific rate email led to an increase of 0.051 percentage points. Although the specific rate treatment effect is more than 50 percent larger than the effect of the baseline email alone, this difference is not statistically significant (p=0.15). Again, the inclusion of individual level controls has little effect on the point estimates.[18]

We next investigate heterogeneity in the effect of the specific rate treatments relative to the baseline treatment on savings behavior along a range of demographic and professional characteristics. With respect to both plan participation (Appendix Table A.2) and average contribution rate (Appendix Table A.3). We observe larger effects for women than for men, for officers than for enlisted servicemembers, and for older compared to younger individuals. However, these differences are either marginally or not statistically significant, depending on the specification.

[17]A possible factor contributing to the effect of the various treatments on savings is that the rate of return calculation example included in the treatments was derived from an annuity calculation using the TSP C-Fund. If this information caused individuals to update their beliefs about the likely return from saving, it could have been that updating, rather than other aspects of the treatment, that caused the increase in saving. However, because both the baseline and specific rate treatments included the same rate of return example, we would not expect this channel to confound the comparison between the specific rate and baseline treatments. Nonetheless, we note the possibility that the observed effect of the specific rate treatments could reflect an interaction between decision costs and beliefs about likely rates of return.

[18]Appendix Table A.1 repeats these analyses, separately estimating the effects of each of the eight specific rate treatment groups. We find that each specific rate treatment leads to a statistically significant increase in both TSP participation and average contribution rates. Additionally, for each of the specific rates, we estimate treatment effects larger in magnitude than those of the baseline treatment for both outcomes.

One concern with light-touch informational interventions like the one considered in this study is that any short-term positive behavioral effects may not persist over time. For example, if our communications solely serve as a reminder to individuals who intended to enroll, they may speed up the timing of enrollment, but will not increase the long-term participation rate. Alternatively, if the marginal participant who enrolls in TSP only because she received our communication turns out to prefer non-participation, we may see a reversal of the treatment effect over time if these enrollees subsequently un-enroll from the program.

Figure 1 plots the estimated effects of the treatment emails on TSP enrollment by quarter during the two years following the intervention, using the regression specification in equation (1).[19] Relative to the control group, the specific rate treatment increases the probability that individuals contribute to the TSP by between 0.61 and 0.77 percentage points in each quarter. The effects of the baseline treatment, relative to the control group, range between 0.36 percentage points and 0.52 percentage points, and are statistically significantly different (at the 10% level) from the control mean in all but the last quarter considered. Relative to the baseline group, assignment to the specific rate group increases the probability that an individual contributes by between 0.16 and 0.30 percentage points; this difference is statistically significant in the first quarter after treatment and remains marginally significant during the first year. Even after the first year, the magnitude of the effect largely persists but there is a reduction in precision due to decreasing sample size as sample members leave the Army and to increasing participation rates among control and treatment groups.

Overall, the results of the analysis in Figure 1 suggests that the immediate effects of the intervention observed in Table 2 largely persist throughout the two-year follow-up period and that the intervention does not merely serve to speed up enrollments, at least not within the two-year window we study.[20] Nonetheless, it may be the case that treatment group

[19]Coefficient estimates corresponding to Figure 1 are contained in Appendix Table A.4.

[20]Appendix Table A.5 complements this analysis by exploring the overall effects of the baseline and specific rate treatments over the two-year time frame on whether individuals ever contribute to their TSP account, the average percent of base pay contributed, and the total savings. We find significant positive effects of the specific rate email on all three measures. The baseline email led to smaller, but statistically significant increases in the average contribution rate and the total savings (though not the participation rate), though

members are more likely to un-enroll shortly after enrolling – for example, if the persistence we estimate incorporates delayed treatment effects on initial enrollments in later quarters of the intervention that are offset by un-enrollments of the early participators. Table 3 investigates this question by comparing the likelihood of stopping contributions in the full sample and among those who enroll in the TSP. We find no evidence that those in either the baseline or specific rate groups stop contributing to the TSP at a higher rate than those in the control; in fact, the point estimates suggest the opposite.

As described in Section IV, our long-run outcomes exclude individuals who have left the Army by the quarter considered. However, it is possible that the intervention affects the likelihood that a servicemember chooses to remain in the Army. Table 4 directly investigates this question by estimating the effect of treatment communications on retention in the Army and finds a precisely estimated null effect.[21]

Decision Costs and Participation

In the results above, we find that both baseline and specific rate treatments increase TSP enrollment but that the specific rate treatments are more effective than the baseline treatment. One explanation for this finding is that the specific rate treatments reduce decision costs: if some individuals who would prefer to save for retirement are uncertain of their optimal contribution rate, then highlighting a specific rate could induce them to participate by simplifying their savings decision, such as by reducing the number of contribution rate options they consider. This section explores whether such decision costs play a role in explaining the decision to enroll in the TSP.

We begin by investigating whether the specific rate treatments had an effect on contribution rate choice relative to the baseline email treatment. For example, if decision costs associated with the selection of a contribution rate prevent individuals from enrolling, re-

we cannot statistically distinguish between the effects of the two communications.

[21]Additionally, Appendix Table A.6 repeats the analyses in Appendix Table A.4 with a constant sample of servicemembers who remained in the Army for all two years and shows that, if anything, the treatment effects are slightly larger for this sample.

ducing those costs would not only increase the share of individuals contributing at positive rates, but would specifically increase the share who contribute at exactly the highlighted rate. To explore this possibility, Figure 2 presents the share of treatment group members who select a given contribution rate, based on the treatment they received. For example, the first set of three bars show (respectively) the share of individuals contributing 1% among those who received the baseline email, the specific rate email that highlighted 1%, and the specific rate emails that highlighted rates other than 1%. For each contribution rate p in the figure, we find that receiving a specific rate treatment of exactly p% increases the likelihood of contributing exactly p% relative to the baseline treatment.[22][23]

In addition to choosing a contribution rate, TSP enrollees can subsequently select a fund allocation. Unlike the contribution rate, which must be actively selected in order to complete enrollment, employees may successfully enroll in TSP without making a fund selection. Those who do not actively select a fund are defaulted into the G-Fund, whereas others can select from one of five funds or lifecycle funds, which are combinations of the primary funds.[24] Table 5 investigates the effects of the two treatment message types on fund allocation. We find no significant effects of the baseline treatment on fund selection. In contrast, we find a marginally significant effect of receiving an email highlighting a specific rate on the likelihood of enrolling in the default fund, but no significant changes in enrolling in a different fund.

Taken together, these results suggest that individuals who are induced to enroll in TSP in response to the specific rate email are more likely to make passive decisions about their

[22]Appendix Table A.7 provides a complementary analysis estimating the effect of each specific rate treatment on the likelihood of contributing exactly p% relative to the baseline treatment. Estimates along the diagonal reveal that increases in the likelihood of contributing exactly p% among those receiving a specific rate treatment of exactly p% are larger in magnitude than the off-diagonal effects and statistically significant for six of the eight specific rate treatments. Given the magnitude of the baseline group mean, these estimates are quite large in percent terms, but small in absolute terms.

[23]All treatments, including the baseline, included an example describing a rate of return calculation based on an investment of $25 per month. Individuals may have interpreted this example as a recommendation or perceived it as an intensive-margin cue. However, our data suggests that this is not the case; $25 translates into a 1% contribution rate for approximately 95% of our sample, yet we do not observe a disproportionate spike in contributions at 1% among the baseline treatment group relative to the control (see Figure 2).

[24]The default fund for uniformed servicemembers remained the G-Fund throughout our study period, though it changed to a life cycle (L) fund in January 2018. This differs from the default fund for civilian participants in the TSP, where the default fund changed from the G-fund to an L-fund in September 2015.

enrollment choices – they are more likely to select exactly the highlighted rate and are more likely to contribute to the default fund. These results are consistent with a model in which decision costs associated with selecting a contribution rate depress TSP participation.

Up to this point our focus has been on identifying the effect of highlighting a specific contribution rate on an individual's extensive margin decision of whether or not to enroll in the TSP. However, it is also possible that this intervention affected the intensive margin decisions of how much an individual chooses to contribute, even among individuals who would have enrolled in the TSP under the baseline treatment. Our experimental design does not permit us to separately identify the extensive and intensive margin effects of the treatments, but does yield some suggestive evidence. For example, if the specific rate treatment generated substantial intensive margin effects, we might observe an (absolute) reduction in the share of individuals selecting positive rates other than the one that was highlighted.[25] However, Figure 2 does not offer any systematic support for this possibility; the share of individuals contributing each rate appears nearly identical under the baseline treatment and under treatments that highlight a different contribution rate.

To more formally summarize the differences in behavior stemming from which specific rate (if any) the individual received, Column 1 of Table 6 considers the stacked regression:

$$y_i^p = \alpha_p + \gamma_0\, SpecificRate_i^p + \gamma_1\, OtherRate_i^p + \gamma_2\, X_i + \varepsilon_i^p \tag{2}$$

where p ranges from 1 to 8, y_i^p indicates that individual i selected contribution rate p, $SpecificRate_i^p$ indicates that i was assigned to the treatment group that highlighted specific rate p, and $OtherRate_i^p$ indicates that i was assigned to a specific rate treatment that highlighted a contribution rate other than p. For this analysis, we exclude individuals who did not receive any email. Note that each individual appears in the regression eight times

[25] In particular, suppose every individual who contributes in the baseline treatment would also contribute in the specified rate treatment. Suppose as well that we observe more individuals contributing at rate $q > 0$ under the baseline treatment than under specific rate treatment $p \neq q$. This would imply that highlighting rate p caused some individuals to switch from q to p – i.e., a positive intensive margin effect.

(one for each value of p); hence, we cluster the reported standard errors at the individual level. The estimated value of γ_0 is positive and statistically significant, which suggests that receiving a specific contribution rate increases the likelihood that an individual chooses to contribute exactly that rate. In particular, the estimated effect is 0.1 percentage points, a 44% increase relative to the average share of individuals who enroll at rates between 1% and 8% under the baseline. The coefficient on γ_1 is close to zero and not statistically significant. Overall, these results of provide no evidence that highlighting a specific rate reduces the share of individuals who select positive rates other than the one that was highlighted.

Thus far we have motivated our analysis and interpreted our results in terms of decision costs. However, an alternative explanation for our finding that the specific rate treatment increases TSP enrollment is a model in which receiving the specific rate treatment causes individuals to update their belief about which contribution rate is optimal for them. For example, the specific rate treatments might cause individuals to change their behavior because they interpret the intervention as advice from their employer or as information about the decisions of their peers (Beshears et al., 2015; Lieber and Skimmyhorn, 2018). That is, an individual may choose not to participate under the baseline treatment because she believes her optimal contribution rate is zero, but updates her belief to some positive contribution rate upon receiving the specific rate treatment. However, if updated beliefs were the main mechanism by which the highlighted rates increased TSP enrollment, one would generally expect the observed increase in contribution rates to be incremental (i.e., between zero and the targeted rate), rather than at the targeted rate itself.[26]

Column 2 of Table 6 investigates this possibility by decomposing the $OtherRate_i^p$ variable in equation (2) into two indicators: $LowerSpecificRate_i^p$, which indicates the highlighted rate assigned to i is less than p, and $HigherSpecificRate_i^p$, which indicates the highlighted

[26]A limitation of this interpretation is that if the marginal enrollees had extremely weak priors about their optimal contribution rates, or if they treated the highlighted rate as an extremely informative signal, one would also expect to observe the increase in positive contribution rates concentrated at the highlighted rate. However, this possibility does not rule out decision costs; it could be that decision costs explain the weakness of individuals' initial priors.

rate assigned to i is greater than p. Although there is a statistically significant increase at contribution rates below the specific rate one receives – consistent with incremental belief-updating driving some of the effect – the increase in the distribution of positive contribution rates is primarily concentrated at the specific rate itself – consistent with decision costs playing some role.

As an additional test of the belief-updating model as an explanation for our results, we next compare the share of individuals participating in the plan (at any contribution rate) among those who received the 1% versus baseline treatments. Although the baseline treatment did not highlight a particular contribution rate, it did endorse participation in the plan (i.e., contributing at some positive rate). Because the minimum contribution rate available to servicemembers was 1%, this theory would predict that individuals receiving the baseline treatment would revise upwards their beliefs about the optimal rate by at least as much as those receiving the 1% treatment. However, Appendix Table A.1 shows that plan participation was higher among the latter group than among the former, in contrast to what a belief-updating model would suggest.[27]

Another possibility is that the specific rate treatments increase participation by introducing new contribution rates into employees' perceived choice set – for example, prior to receiving the communication, individuals may not have considered the possibility of participating at very low contribution rates, like 1 or 2%. Evidence consistent with this explanation is that the lowest specific rate treatments are associated with the largest point estimates (Appendix Table A.1) (although the difference in estimated effects between the different specific rate treatments is only marginally significant). To assess whether this mechanism is driving our results, Appendix Table A.8 replicates Table 2 excluding the lowest specific rates treatments (1 and 2%). Even excluding the lower specific rate treatments, we still find that

[27] To the extent that recipients interpret the baseline treatment as containing an (unspecified) positive contribution rate recommendation, this finding also provides some evidence against a pure anchoring explanation of our results, since the anchoring force of the baseline treatment would be at least as strong as the pull of the 1% treatment. On the other hand, it is also possible that the strength of the baseline treatment as an anchor is diminished by the absence of a specific highlighted rate.

receiving a specific rate treatment had a larger effect on participation than the baseline treatment, consistent with decision costs playing a role.

Finally, it could be that the information about other servicemembers' decisions contained in the specific rate treatments affected servicemembers' behavior by creating or reinforcing a descriptive social norm in favor of TSP participation. Although we cannot rule this mechanism out, recent research suggests that peer effects tend not to be effective (and may in fact backfire) at increasing the savings rate among low-saving populations like the one we study (Beshears et al., 2015; Lieber and Skimmyhorn, 2018; Dur et al., 2019). In addition, the fact that the marginal enrollees from the specific rate treatments choose passively with respect to their fund allocation (Table 5) is consistent with a model of decision costs operating as a barrier to enrollment but would not be implied by a model driven by social norms (since the letters do not describe the funds chosen by other servicemembers).

VI. Conclusion

We evaluate a randomized intervention to encourage retirement plan participation among a population whose lack of savings is a subject of significant policy concern: active-duty servicemembers. We find positive and persistent effects of communications encouraging retirement savings on plan participation, with larger effects from communications that highlight a specific contribution rate. On the one hand, these effects were modest in magnitude, and unlikely to be a complete solution to the problem of under-saving among this population. On the other hand, the financial cost of the communication, and in particular the incremental cost of highlighting a specific rate, were close to zero. Moreover, the presence of any effect is striking given that the average servicemember in our sample has had 6 years to enroll and most have received prior communications urging enrollment (Benartzi et al., 2017).

Like many choices, retirement saving decisions can be complicated across multiple dimensions. Our results suggest that reducing complexity along one of these dimensions – e.g., which rate to contribute to a retirement saving plan – can affect how individuals behave with respect to related decisions – e.g., whether to enroll in the plan at all. For example, at the time of our intervention, new TSP enrollees who did not select an investment fund were defaulted into the G-Fund. Our results suggest that by reducing the complexity of this dimension of the retirement savings decision (the choice of fund), this aspect of the plan's design may have increased participation.

An important limitation of our analysis is that we lack data on the share of servicemembers who opened or read the treatment communications. This information would allow us to better interpret the magnitude of our estimated treatment effect by identifying the share of readers who changed their behavior in response to the intervention. Drawing on readership estimates from prior studies with similar populations, our best guess is that our observed intent-to-treat effect represents a substantial change in behavior among those servicemembers who read the communication. For example, assuming that 5.6% of servicemembers read the treatment communications (as in Castleman, Patterson and Skimmyhorn (2019)), our results suggest that among this population, the baseline and specific rate treatments led to participation increases of 7 and 13 percentage points, respectively.

Although we find that highlighting a specific contribution rate can raise TSP enrollment, our results do not directly address the question of which rate should be highlighted to maximize welfare. In particular, two types of challenges make addressing this question quite difficult in our setting. First, we lack reliable welfare information about the saving preferences of our sample members. For those whose enrollment decisions hinge on whether they receive a highlighted contribution rate, their revealed preferences are inconclusive with respect to which contribution rates will best further their welfare.[28] A second challenge for drawing welfare conclusions from our experimental data is that we do not observe non-TSP

[28]This is true under the assumption that individuals' normative preferences about how much to save do not themselves depend upon whether a highlighted rate is included in the email they receive. An interesting feature of our setting is that the researcher does observe contribution rate decisions by individuals assigned to the baseline group that are uncontaminated by any specific highlighted rate; however, if those affected by the highlighted rate have a different distribution of contribution rate preferences than this group, additional data or assumptions are needed to extrapolate from the latter to the former (see Goldin and Reck (2020)).

savings or debt. Thus, we cannot rule out the possibility that some of the additional savings associated with enrolling in the TSP are offset by reducing savings through other vehicles or even new debt, although Beshears et al. (2019) provide evidence that shifting towards costly forms of debt (e.g., credit cards) is unlikely.

Although our results do not directly yield the optimal contribution rate to highlight in communications, they do shed light on some related issues. For example, a potential concern with highlighting a specific contribution rate is that it could distort intensive margin contribution decisions by "pulling" them towards the highlighted rate. In this scenario, the specific rate treatments might improve welfare for those it induces to enroll in the TSP, but reduce welfare for those who would have enrolled even under the baseline treatment, but whose contribution rate is distorted from what they would have (otherwise) optimally selected.[29] However, our results provide no evidence that highlighting a specific rate affects the choices of those who would have participated under the baseline treatment.

We have focused on the effect of complexity on decision-making in the retirement savings context, but similar phenomena may apply in other areas as well. With respect to charitable contributions, for example, Edwards and List (2014) suggests that decision costs associated with determining how much to donate affects whether individuals choose to make any donation at all. It is easy to imagine a similar story in health insurance markets. Prior research has documented that the complexity of purchasing health insurance results in sub-optimal consumer choices (Abaluck and Gruber, 2011; Kling et al., 2012; Bhargava, Loewenstein and Sydnor, 2017); our results suggest this complexity might also reduce the rate at which consumers enroll in health insurance coverage at all. More broadly, one could imagine intensive margin complexity plays an important role in decisions ranging from choices about whether to attend college, switch jobs, or move homes.

[29] For example, Goda et al. (2019) find that improving the default fund allocation increases the likelihood of choosing the default contribution rate rather than the rate that maximizes the employer match.

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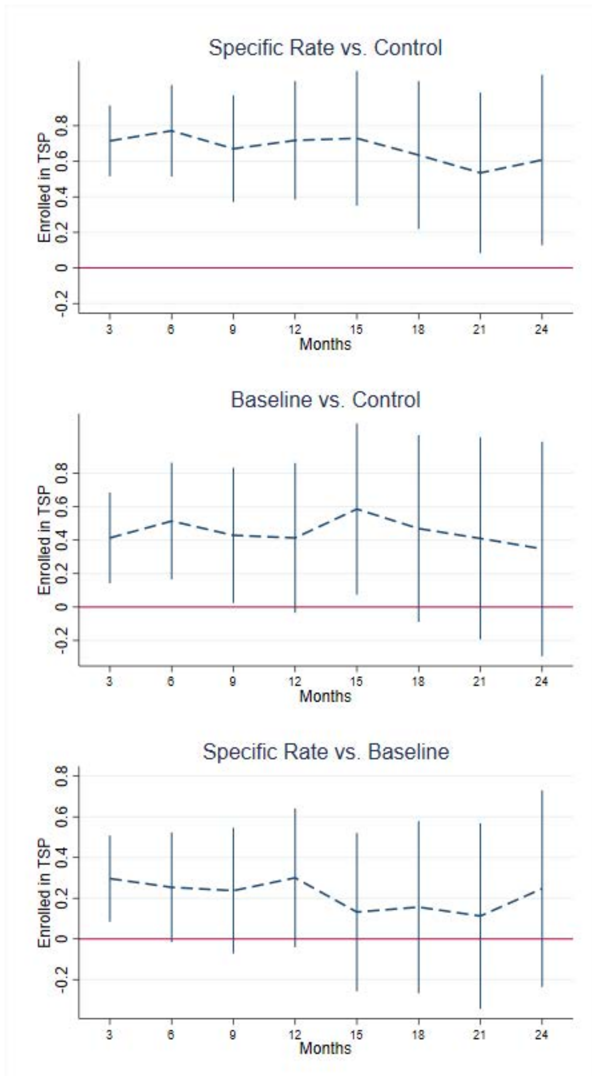
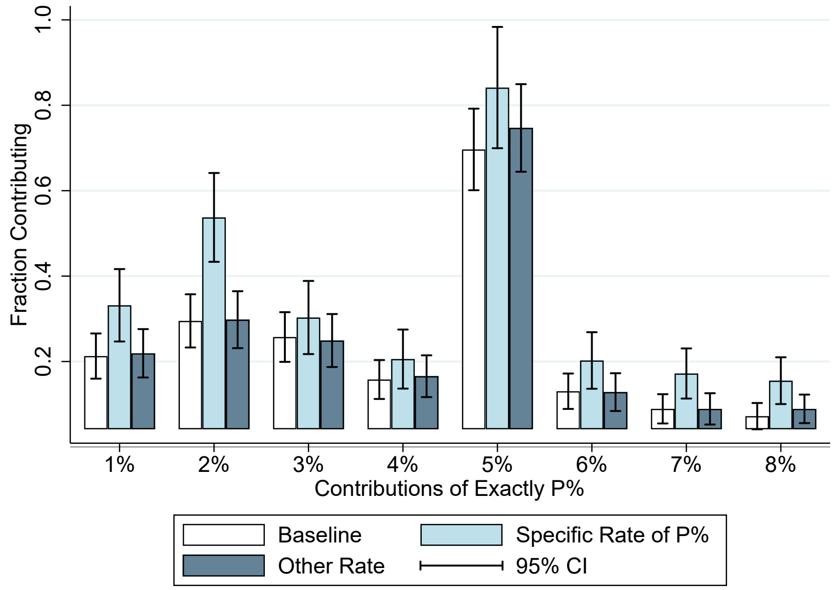
Tables and Figures

Figure 1: Treatment Effects by Time



Notes: Figure presents treatment effects for the likelihood of contributing to the TSP in the given quarter following the intervention for the baseline treatment (Panel A), the specific rate treatment (Panel B), and the difference between the baseline and specific rate treatments (Panel C). Units are in percentage points (0-100). Bars represent the 95% confidence intervals.

Figure 2: Contribution Rate Choices by Treatment



Note: Each set of three bars presents the fraction of servicemembers contributing exactly P% in the first quarter following the intervention among three groups of servicemembers: those assigned to the baseline group (white), the specific rate group that highlighted P% (light blue), and the specific rate groups that highlighted a rate other than P% (dark blue). Units are in percentage points (0-100). Bars represent the 95% confidence interval.

Table 1: Summary Statistics and Randomization Checks

	No Email	Baseline	Specific Rate	P-value
Female	0.133	0.131	0.132	0.074
	(0.340)	(0.338)	(0.338)	
Age	27.48	27.40	27.43	0.785
	(7.70)	(7.64)	(7.66)	
Black	0.208	0.209	0.211	0.114
	(0.406)	(0.407)	(0.408)	
Hispanic	0.145	0.149	0.146	0.181
	(0.352)	(0.356)	(0.353)	
Other Race/Ethnicity	0.074	0.071	0.071	0.256
	(0.261)	(0.257)	(0.257)	
Married	0.516	0.517	0.518	0.688
	(0.500)	(0.500)	(0.500)	
Divorced	0.040	0.043	0.041	0.315
	(0.196)	(0.202)	(0.198)	
Number of Children	1.000	0.990	0.993	0.206
	(1.176)	(1.181)	(1.181)	
Some College	0.128	0.128	0.130	0.638
	(0.334)	(0.334)	(0.336)	
Bachelors Degree+	0.184	0.181	0.181	0.593
	(0.388)	(0.385)	(0.385)	
AFQT Score	57.80	57.76	57.91	0.215
	(18.91)	(18.79)	(18.87)	
Years of Service	6.26	6.21	6.23	0.419
	(6.52)	(6.43)	(6.46)	
Enlisted	0.858	0.858	0.858	0.533
	(0.349)	(0.350)	(0.349)	
Monthly Base Pay	2,993	2,984	2,989	0.217
	(1,568)	(1,560)	(1,564)	
N	29,084	29,142	233,311	

Table reports sample means by experimental group. P-Values presented in column 4 are associated with an F-test for equality across all 10 experimental groups: Control, Baseline, and each Specific Rate group of 1 through 8 percent.

Table 2: Treatment Effects on TSP Contributions

	Ever Contribute (1)	(2)	Contribution Rate (3)	(4)
Baseline	0.417***	0.417***	0.032*	0.033**
	(0.139)	(0.139)	(0.017)	(0.017)
Specific Rate	0.714***	0.714***	0.051***	0.052***
	(0.102)	(0.102)	(0.012)	(0.012)
N	291,537	291,537	287,458	287,458
Specific Rate vs. Baseline P-value	0.006	0.006	0.145	0.148
Control Group Mean	2.706	2.706	0.225	0.225
Control Variables	N	Y	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. "Ever contribute" is an indicator for enrolling in TSP in the first quarter following the intervention with units in percentage points (0-100). "Contribution rate" is the maximum TSP contribution rate selected in the first quarter following the intervention, with non-participants receiving a value of zero. Control variables include age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Table 3: Treatment Effect on Stopping Contributions

	Full Sample (1)	(2)	Conditional on Contributing (3)	(4)
Baseline	-0.145	-0.145	-1.107	-0.971
	(0.142)	(0.141)	(0.851)	(0.844)
Specific Rate	-0.121	-0.120	-1.195*	-1.025
	(0.108)	(0.107)	(0.648)	(0.642)
N	207,701	207,701	33,193	33,193
Specific Rate vs. Baseline P-value	0.818	0.807	0.889	0.931
Control Group Mean	2.197	2.197	14.121	14.121
Control Variables	N	Y	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Outcome is an indicator for having enrolled and subsequently unenrolled in the TSP during the two years following the intervention. Units are in percentage points (0-100). Columns 1 and 2 include the full experimental sample; columns 3 and 4 restrict the sample to those who ever enrolled in the TSP during the two years following the intervention. Analysis excludes all servicemembers who left the Army within two years of intervention. Control variables include age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Table 4: Effects of Treatments on Retention in Army

	Two Months	6 Months	12 Months	18 Months	24 Months
Baseline	-0.101	-0.072	0.004	0.205	0.223
	(0.137)	(0.172)	(0.191)	(0.196)	(0.196)
Specific Rate	0.008	0.069	0.048	0.187	0.208
	(0.102)	(0.129)	(0.144)	(0.148)	(0.148)
N	291,537	291,537	291,537	291,537	291,537
Specific Rate vs. Baseline P-value	0.296	0.277	0.758	0.901	0.917
Control Group Mean	96.899	92.250	83.795	76.960	71.036

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Outcome is an indicator for having remaining in the Army through the start of the given quarter following the intervention. Units are in percentage points (0-100). All regressions include controls for age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Table 5: Treatment Effects on Fund Allocation

	G-Fund Gov Bond	F-Fund Bonds	C-Fund Stocks	S-Fund Small Cap	I-Fund International	L-Fund Lifecycle
Baseline	0.265	-0.015	-0.029	-0.057	-0.039	-0.095
	(0.354)	(0.080)	(0.157)	(0.143)	(0.125)	(0.226)
Specific Rate	0.499*	0.014	-0.066	-0.022	-0.032	-0.139
	(0.265)	(0.060)	(0.118)	(0.108)	(0.094)	(0.170)
N	207,701	207,701	207,701	207,701	207,701	207,701
Specific Rate vs. Baseline P-value	0.380	0.626	0.748	0.738	0.937	0.791
Control Group Mean	16.193	0.658	2.657	2.173	1.636	5.716

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Outcome variables are indicators for contributing to the given fund within the two years following the intervention with units in percentage points. Analysis includes all sample members who remained in the Army throughout the two years following the intervention. Fund options include: G-Fund (government bonds), F-Fund (fixed income including an index of corporate bonds), C-fund (managed to replicate the S&P 500), S-Fund (managed to replicate the Dow Jones U.S. Completion Total Stock Market Index), I-Fund (managed to replicate MSCI EAFE international Index), and L-Fund (includes several TSP lifecycle fund options). The G-Fund is the default for those who do not select a specific fund. All regressions include controls for age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Table 6: Treatment Effect on Contribution Rate Choices

	(1)	(2)
Specific Rate of P	0.105***	0.105***
	(0.016)	(0.016)
Other Rate Group	0.009	
	(0.011)	
Higher Specific Rate		0.027**
		(0.012)
Lower Specific Rate		-0.009
		(0.011)
N	262,453	262,453
Baseline Group Mean	0.239	0.239

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors in parentheses. 2,099,624 specific rate by individual observations are clustered at the individual level (N=262,453). Results presented for the stacked regression in which the outcome is an indicator for contributing exactly P% at the end of the first quarter following the intervention. "Specific Rate of P" is an indicator for assignment to the specific rate treatment group that highlighted a rate of P%; "Other Rate Group" is an indicator for assignment to a specific rate treatment group that highlighted a rate other than P%; "Higher Specific Rate" is an indicator for assignment to a specific rate treatment group that highlighted a rate higher than P%; "Lower Specific Rate" is an indicator for assignment to a specific rate treatment group that highlighted a rate lower than P%. Units are in percentage points (0-100). Analysis excludes servicemembers assigned to the control group and those who have left the Army by the end of the first quarter. All regressions include controls for age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

A Appendix

Table A.1: Effect on TSP Contributions by Treatment Group

	Ever Contribute		Contribution Rate	
	(1)	(2)	(3)	(4)
Baseline	0.417***	0.417***	0.032*	0.033**
	(0.139)	(0.139)	(0.017)	(0.017)
1% Group	0.932***	0.952***	0.062***	0.064***
	(0.145)	(0.145)	(0.018)	(0.017)
2% Group	0.897***	0.887***	0.046***	0.046***
	(0.144)	(0.143)	(0.017)	(0.017)
3% Group	0.773***	0.782***	0.057***	0.058***
	(0.143)	(0.142)	(0.017)	(0.017)
4% Group	0.682***	0.676***	0.058***	0.057***
	(0.142)	(0.142)	(0.018)	(0.017)
5% Group	0.618***	0.616***	0.045***	0.045***
	(0.142)	(0.141)	(0.017)	(0.017)
6% Group	0.602***	0.587***	0.047***	0.046***
	(0.142)	(0.141)	(0.017)	(0.017)
7% Group	0.605***	0.606***	0.057***	0.058***
	(0.142)	(0.141)	(0.017)	(0.017)
8% Group	0.599***	0.604***	0.037**	0.038**
	(0.142)	(0.141)	(0.016)	(0.016)
N	291,537	291,537	287,458	287,458
Joint Specific Rate P-value	0.122	0.089	0.867	0.829
Control Group Mean	2.706	2.706	0.225	0.225
Control Variables	N	Y	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. "Ever contribute" is an indicator for enrolling in TSP in the first quarter following the intervention with units in percentage points. "Contribution rate" is the maximum TSP contribution rate selected in the first quarter following the intervention, with non-participants receiving a value of zero. Control variables include age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Table A.2: Heterogeneous Treatment Effects - Participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8))
Specific Rate	0.3015*	0.3407**	0.6412**	0.1607	0.2802**	0.2205*	0.3351**	0.6044
	(0.1703)	(0.1597)	(0.2924)	(0.1624)	(0.1387)	(0.1129)	(0.1542)	(0.3813)
Specific Rate*High Experience	-0.0155							-0.1696
	(0.2151)							(0.3447)
Specific Rate*High Salary		-0.0929						-0.3277
		(0.2162)						(0.3298)
Specific Rate*Enlisted			-0.4114					-0.4205
			(0.3195)					(0.3325)
Specific Rate*High Age				0.2774				0.6345*
				(0.2149)				(0.3277)
Specific Rate*Non-White					0.0367			0.0061
					(0.2206)			(0.2240)
Specific Rate*Female						0.5644		0.5490
						(0.3640)		(0.3686)
Specific Rate*Has Children							-0.0952	-0.2069
							(0.2125)	(0.2671)
N	262,453	262,453	262,453	262,453	262,453	262,453	262,453	262,453
Baseline Group Mean	3.123	3.123	3.123	3.123	3.123	3.123	3.123	3.123

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. In all columns, the outcome indicates enrolling in TSP during the first quarter following the intervention; units are percentage points (0-100). All columns include controls for age, sex, race, marital status, education, AFQT score, years of service, and enlisted status. High experience indicates above-median experience (3 years or more). High salary indicates above-median salary ($4,004 per month or more). High age indicates above-median age (25 years or older).

Table A.3: Heterogeneous Treatment Effects - Contribution Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specific Rate	0.0152	0.0119	0.0958**	0.0005	0.0221	0.0132	0.0188	0.0911
	(0.0215)	(0.0191)	(0.0469)	(0.0201)	(0.0171)	(0.0137)	(0.0196)	(0.0576)
Specific Rate*High Experience	0.0070							-0.0242
	(0.0257)							(0.0428)
Specific Rate*High Salary		0.0133						-0.0165
		(0.0260)						(0.0434)
Specific Rate*Enlisted			-0.0905*					-0.0880*
			(0.0492)					(0.0480)
Specific Rate*High Age				0.0380				0.0608*
				(0.0257)				(0.0366)
Specific Rate*Non-White					-0.0078			-0.0053
					(0.0263)			(0.0255)
Specific Rate*Female						0.0416		0.0408
						(0.0415)		(0.0420)
Specific Rate*Has Children							-0.0005	-0.0220
							(0.0248)	(0.0307)
N	258,774	258,774	258,774	258,774	258,774	258,774	258,774	258,774
Baseline Group Mean	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. In all columns, the outcome is the maximum TSP contribution rate selected in the first quarter following the intervention, with non-participants receiving a value of zero. All columns include controls for age, sex, race, marital status, education, AFQT score, years of service, and enlisted status. High experience indicates above-median experience (3 years or more). High salary indicates above-median salary ($4,004 per month or more). High age indicates above-median age (25 years or older).

Table A.4: Quarterly Effects of Treatments on TSP Contributions

	3 Months	6 Months	12 Months	18 Months	24 Months
Baseline	0.417***	0.517***	0.418*	0.479*	0.360
	(0.139)	(0.178)	(0.229)	(0.285)	(0.327)
Specific Rate	0.714***	0.771***	0.718***	0.635***	0.608**
	(0.102)	(0.131)	(0.170)	(0.212)	(0.245)
N	291,537	277,840	251,584	230,762	211,069
Specific Rate vs. Baseline P-value	0.006	0.065	0.085	0.468	0.314
Control Group Mean	2.706	4.435	7.014	10.522	13.242

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Outcome is an indicator for having enrolled in the TSP during the given quarter following the intervention. Units are in percentage points (0-100). Analysis excludes all servicemembers who left the Army before the start of the given quarter. All regressions include controls for age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Table A.5: Long-Run Cumulative Effects of Treatments on TSP Contributions

	Ever Contribute		Contribution Rate		Savings	
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline	0.208	0.237	0.040**	0.043**	41.461*	42.673*
	(0.358)	(0.350)	(0.020)	(0.020)	(24.324)	(23.835)
Specific Rate	0.501*	0.544**	0.054***	0.057***	51.432***	54.172***
	(0.268)	(0.263)	(0.015)	(0.015)	(17.907)	(17.543)
N	207,701	207,701	207,225	207,225	207,701	207,701
Specific Rate vs. Baseline P-value	0.276	0.243	0.381	0.362	0.591	0.527
Control Group Mean	15.767	15.767	0.578	0.578	573.6	573.6
Control Variables	N	Y	N	Y	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. "Ever contribute" is an indicator for ever having enrolled in TSP during the two years following the intervention with units in percentage points. "Contribution rate" is the average monthly TSP contribution rate across the two-year intervention, with non-participants receiving a value of zero. "Savings" is the total TSP contributions in dollars during the two years following the intervention. Analysis excludes all servicemembers who left the Army before the end of the two-year intervention. Control variables include age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Table A.6: Long-Run Effects of Treatments on Contributions, Constant Sample

	3 Months	6 Months	12 Months	18 Months	24 Months
Baseline	0.584***	0.614***	0.462*	0.507	0.378
	(0.184)	(0.226)	(0.267)	(0.309)	(0.331)
Specific Rate	0.857***	0.876***	0.779***	0.697***	0.661***
	(0.134)	(0.167)	(0.198)	(0.231)	(0.248)
N	207,701	207,701	207,701	207,701	207,701
Specific Rate vs. Baseline P-value	0.058	0.132	0.117	0.417	0.256
Control Group Mean	3.397	5.391	7.932	11.262	13.362

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Outcome is an indicator for having enrolled in the TSP in the given quarter following the intervention. Units are in percentage points (0-100). Analysis excludes all servicemembers who left the Army before the start of the given quarter. All regressions include controls for age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Table A.7: Contribution Rate Choices: Baseline vs. Specific Rate

Contribution Levels	1%	2%	3%	4%	5%	6%	7%	8%
1% Rate Group	0.119***	0.119**	-0.026	-0.009	0.112	0.004	0.008	0.014
	(0.043)	(0.049)	(0.041)	(0.032)	(0.072)	(0.030)	(0.025)	(0.023)
2% Rate Group	0.034	0.242***	0.033	0.042	0.145**	-0.005	-0.018	0.006
	(0.040)	(0.053)	(0.043)	(0.035)	(0.072)	(0.029)	(0.023)	(0.023)
3% Rate Group	0.039	-0.016	0.046	0.023	0.022	0.016	-0.018	0.040
	(0.040)	(0.044)	(0.044)	(0.034)	(0.069)	(0.031)	(0.023)	(0.025)
4% Rate Group	-0.000	-0.055	-0.010	0.048	0.068	0.007	-0.003	0.041
	(0.038)	(0.043)	(0.042)	(0.035)	(0.071)	(0.030)	(0.024)	(0.025)
5% Rate Group	0.011	-0.057	0.015	0.028	0.145**	0.004	0.004	0.018
	(0.039)	(0.043)	(0.043)	(0.034)	(0.072)	(0.030)	(0.025)	(0.024)
6% Rate Group	0.003	-0.000	-0.000	-0.000	-0.017	0.072**	0.021	-0.007
	(0.038)	(0.045)	(0.042)	(0.033)	(0.068)	(0.034)	(0.026)	(0.022)
7% Rate Group	-0.024	0.007	-0.044	-0.041	0.029	-0.038	0.083***	0.007
	(0.037)	(0.045)	(0.040)	(0.031)	(0.070)	(0.028)	(0.030)	(0.023)
8% Rate Group	-0.020	0.022	-0.026	0.011	-0.007	-0.003	-0.003	0.083***
	(0.037)	(0.046)	(0.041)	(0.033)	(0.069)	(0.030)	(0.025)	(0.028)
N	262,453	262,453	262,453	262,453	262,453	262,453	262,453	262,453
Baseline Group Mean	0.213	0.295	0.257	0.158	0.697	0.130	0.089	0.072

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. Outcome is an indicator for contributing exactly P% in the first quarter following the intervention. Units are in percentage points (0-100). Analysis excludes control group members; estimated treatment effects are relative to the baseline group. All regressions include controls for age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Table A.8: Treatment Effects on TSP Contributions, Omitting 1 and 2 Percent Groups

	Ever Contribute		Contribution Rate	
	(1)	(2)	(3)	(4)
Baseline	0.417***	0.417***	0.032*	0.033**
	(0.139)	(0.139)	(0.017)	(0.017)
Specific Rate	0.647***	0.646***	0.050***	0.051***
	(0.104)	(0.104)	(0.012)	(0.012)
N	233,006	233,006	229,738	229,738
Specific Rate vs. Baseline P-value	0.037	0.038	0.173	0.182
Control Group Mean	2.706	2.706	0.225	0.225
Control Variables	N	Y	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Analyses omit 1 and 2 percent specific rate treatment groups. Robust standard errors in parentheses. "Ever contribute" is an indicator for enrolling in TSP in the first quarter following the intervention with units in percentage points (0-100). "Contribution rate" is the maximum TSP contribution rate selected in the first quarter following the intervention, with non-participants receiving a value of zero. Control variables include age, sex, race, marital status, education, AFQT score, years of service, and enlisted status.

Figure A.1: Sample Messages

(a) Baseline

Subject: Military TSP: Our Records Indicate You Aren't Enrolled

Now is the perfect time for Servicemembers like you to take action to ensure you don't lose out on a secure future by investing with a Thrift Savings Plan (TSP). TSP is like a 401k, available exclusively to military Servicemembers and government employees. Invest in your future with TSP: if you'd put away just $25 a month starting in 1980, it'd be worth over $66,700 today.

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Do you want sign up to save?

YES, I WANT TO SAVE THROUGH TSP! Follow these simple steps (<5 mins):

(1) Log in at mypay.dfas.mil*

(2) Click on the "Traditional TSP and Roth TSP" link.

(3) Enter the percentage of your basic, special, incentive, and bonus pay that you want to contribute, follow the instructions to submit and you're done!

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* If you prefer a paper form, complete the TSP-U-1 form at www.tsp.gov; this website also has information on Traditional versus Roth TSP and investment options; or you can visit with your installation personal financial manager.

(b) Specific Rate

Subject: Military TSP: Our Records Indicate You Aren't Enrolled

Now is the perfect time for Servicemembers like you to take action to ensure you don't lose out on a secure future by investing with a Thrift Savings Plan (TSP). TSP is like a 401k, available exclusively to military Servicemembers and government employees. Invest in your future with TSP: if you'd put away just $25 a month starting in 1980, it'd be worth over $66,700 today.

MANY SERVICEMEMBERS LIKE YOU START BY CONTRIBUTING AT LEAST 8% OF THEIR BASIC PAY INTO A TRADITIONAL OR ROTH TSP ACCOUNT.

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Do you want sign up to save?

YES, I WANT TO SAVE THROUGH TSP! Follow these simple steps (<5 mins):

(1) Log in at mypay.dfas.mil*

(2) Click on the "Traditional TSP and Roth TSP" link.

(3) Enter the percentage of your basic, special, incentive, and bonus pay that you want to contribute, follow the instructions to submit and you're done!

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* If you prefer a paper form, complete the TSP-U-1 form at www.tsp.gov; this website also has information on Traditional versus Roth TSP and investment options; or you can visit with your installation personal financial manager.